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**STRUCTURES OF MEMORY
FOR CRITICAL FLIGHT INFORMATION**

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the training program of fighter pilots and in assessing individual differences in the development of appropriate conceptual structures.

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This paper is published in the interest of scientific and technical information exchange; the basic research reported represents an early stage in the development of cognitive structures for flight-related information.

SUMMARY

Objective

The objective was information concerning the organization of pilots' memories for critical flight related information and a description of any systematic differences in memory structure that were related to differences in flying experience.

Background/Rationale

Research into natural language has suggested that retrieval of information from memory is affected by the organization of memory. More rapid and effective retrieval can result from a more efficient and economical storage structure. The organization of information in memory can have a critical impact on flying performance. Understanding how critical information is organized in memory can be extremely useful to training program designers and evaluators as well as instructors and others interested in increasing the effectiveness of the pilot-aircraft system. Knowledge of how individuals develop systems for organizing critical information can be used to tailor training systems to provide students the conceptual framework that will lead to optimal learning. It may also provide a useful selection tool by allowing instructors to determine which individuals have mastered the prerequisite concepts for success in a particular training program.

Approach

Two sets of stimulus materials displayed on the console of a Terak 8510/A microcomputer were presented to four groups of officers: Air National Guard pilots (GPs), Fighter Lead-in Instructor pilots (IPs), recent Undergraduate Pilot Training (UPT) graduates, and Instructor Weapons System Officers (WSOs). Three statistical techniques (hierarchical cluster analysis, multi-dimensional scaling (MDS) and general weighted network were used to analyze the data and describe the cognitive structure of the groups studied.

Specifics

Subjects were nine A-7 GPs from the Colorado Air National Guard, seven Fighter Lead-in IPs, four Fighter Lead-in Instructor WSOs, and 17 recent UPT Graduates. The GPs each had in excess of 2000 hours flying time. The IPs had 1200-4900 hours, and the UPT graduates had about 200 hours. Although the GPs and IPs had roughly similar amounts of flying time, their experience differed in that the GPs had little instructor experience while the IPs had relatively less operational experience. The WSOs had 800-3000 hours.

Two conceptual sets were investigated. One, the low-angle strafe, was related to only a single maneuver. The other set dealt with a class of maneuvers: the split-plane maneuvers. The stimulus sets were generated by the experimenters working with senior IPs at Holloman AFB. Populations of flight related terms were assembled through interviews with IPs at Holloman AFB. These were condensed to one set of 30 stimulus items for split-plane and 30 for strafe.

Subjects performed a self-paced rating task in which all pair-wise combinations of the items in each set were rated for similarity. Similarity ratings were treated as distances in conceptual space. In addition, the UPTs gave a rating of their familiarity with the terms. This was done to ensure that the UPT graduates had at least a minimal degree of familiarity with the terms.

Analyses showed the more experienced pilots to have conceptual structures that were better developed, more sophisticated, and more economical than the UPT graduates. The WSOs were also found to have conceptual structures which differed from those of the pilots.

A pattern recognition algorithm was applied to the MDS solutions and to the raw rating data to see if the groups could be distinguished on the basis of their conceptual structures. This program searched for a pattern or

prototype which characterized the conceptual structure of members of a group. The groups were found to have different conceptual structures, with the more experienced individuals showing a slightly greater tendency to cluster about the group prototype, while the recent UPT graduates tended to be more diverse.

Conclusions/Recommendations

1. Pilots do have measurable cognitive structures for remembering and recalling flight related information.
2. Cognitive structures show measurable differences as a function of flying experience. Experienced pilots exhibit more efficient and economical organization of flight related information than do less experienced pilots. The WSOs showed a memory structure that differed from that of the pilots.
3. The approach used in the present research can provide a useful tool for looking at differences in individuals' understanding of flying tasks. Such a tool may have application both for assessing individual differences in the development of conceptual understanding during learning and for looking at the effectiveness of training programs in conveying critical flight related concepts to students.

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TABLE OF CONTENTS

INTRODUCTION.....	1
GENERATION OF STIMULUS MATERIALS.....	5
SIMILARITY-RELATEDNESS RATINGS.....	10
HIERARCHICAL CLUSTERING.....	18
MULTIDIMENSIONAL SCALING.....	24
PATTERN RECOGNITION ANALYSIS OF CONCEPTUAL STRUCTURES.....	34
GENERAL WEIGHTED NETWORKS.....	58
GENERAL DISCUSSION.....	84
REFERENCES.....	90
APPENDIX.....	93

LIST OF ILLUSTRATIONS

Figure	Description	Page
1	Hierarchy of Natural Language Concepts.....	2
2	Hierarchical Clusters - Split-Plane Concepts - IPs..	19
3	Hierarchical Clusters - Split-Plane Concepts - UPs..	20
4	Hierarchical Clusters - Strafe Concepts - IPs.....	21
5	Hierarchical Clusters - Strafe Concepts - UPs.....	22
6	MDS Solution - Split-Plane Concepts - IPs.....	25
7	MDS Solution - Split-Plane Concepts - UPs.....	26
8	MDS Solution - Strafe Concepts - IPs.....	27
9	MDS Solution - Strafe Concepts - UPs.....	28
10	Minimum Connected Network - Split-Plane - IPs.....	60
11	Minimum Elaborated Network - Split-Plane - IPs.....	61
12	Cycles in the Network - Split-Plane - IPs.....	62
13	Minimum Elaborated Network - Split-Plane - UPs.....	63
14	Minimum Elaborated Network - Strafe - IPs.....	64
15	Minimum Elaborated Network - Strafe - UPs.....	65
16	Assemblies in the Network - Split-Plane - IPs.....	66
17	Clusters in a Multidimensional Structure.....	87

LIST OF TABLES

Table	Description	Page
1	Concepts from Split-Plane Maneuvers.....	7
2	Concepts from Low Angle Strafe Maneuver.....	8
3	Essential Aircraft Terms.....	9
4	Subject Groups for the Rating Task.....	11
5	Flying Time for Individual Subjects.....	12
6	Familiarity of UPs with Each Concept.....	14
7	Familiarity of Individual UPs with all Concepts.....	15
8	Rating Score Correlations for IPs.....	17
9	Concept Clusters for IPs and UPs - Split-Plane.....	23
10	Dimensions in the Multidimensional Solutions.....	30
11	Within and Between Group Correlations - Split-Plane...	32
12	Within and Between Group Correlations - Strafe.....	33
13	Classifications with the Minimum-Distance Classifier..	38
14	Distances between Group Prototypes.....	40
15	Analysis of Individual IPs - Split-Plane.....	42
16	Analysis of Individual GPs - Split-Plane.....	43
17	Analysis of Individual IWs - Split-Plane.....	44
18	Analysis of Individual UPs - Split-Plane - Ratings....	45
19	Analysis of Individual UPs - Split-Plane - MDS.....	46
20	Analysis of Individual IPs - Strafe.....	47
21	Analysis of Individual IWs - Strafe.....	48
22	Analysis of Individual UPs - Strafe - Ratings.....	49
23	Analysis of Individual UPs - Strafe - MDS.....	50
24	Predictions of Group Membership - Split-Plane.....	53
25	Predictions of Group Membership - Split-Plane.....	54
26	Predictions of Group Membership - Strafe.....	55
27	Pairs of Concepts that Discriminate IPs and UPs.....	57
28	Dominating Concepts and Assemblies.....	71
29	Comparison of Novice and Expert Concepts.....	81
30	Erroneous Links in the Novice Network.....	82

INTRODUCTION

In the past decade, experimental psychologists have generated a considerable body of theory and data concerning the organization and retrieval of knowledge in human memory. This research area (which has come to be known as semantic memory) has concentrated largely on the study of natural categories and their members (e.g., birds, minerals, geological formations). One of the first theoretical proposals in the area was suggested by Collins and Quillian (1969) following the lead developed by Quillian (1969) in the form of an intelligent, question-answering computer system.

Two important structural principles were embodied in the theoretical analysis offered by Collins and Quillian: hierarchical organization and cognitive economy. The hierarchical principle refers to the proposal that concepts are stored in memory as nodes in a network with each node having labeled links to other nodes that represent superordinate concepts. For example, the node representing the concept "robin" would have a particular kind of link (ISA) to the node representing the concept "bird." The hierarchical scheme requires that each concept only be connected to its immediate superordinate and not to more general concepts (e.g., robin is directly connected to bird but not to animal). The hierarchy also provides a basis for inferences about facts not learned directly. If the structure contains the facts that "an A is a B" and "a B is a C", then it can be inferred that "an A is a C."

The principle of cognitive economy refers to the way in which properties of concepts are represented in the memory system. In particular, properties are stored at the highest possible level of the hierarchy. This means that properties pertaining to all members of a particular category need to be stored only once with a link to the node representing the category. For example, the property "has wings" would be stored with the concept bird rather than with each particular type of bird. Thus there is an economy of storage. Both principles are illustrated in the network structure shown in Figure 1.

Collins and Quillian (1969, 1970) presented evidence favoring the hierarchical theory of human memory structure. They showed that people were faster in verifying true sentences relating concepts near in the hierarchy (e.g., A robin is a bird.) compared to sentences relating more distant concepts (e.g., A robin is an animal.). Similar results were found for sentences asserting property relations. Those sentences were also verified more slowly when the noun and the property were further apart in the hierarchy.

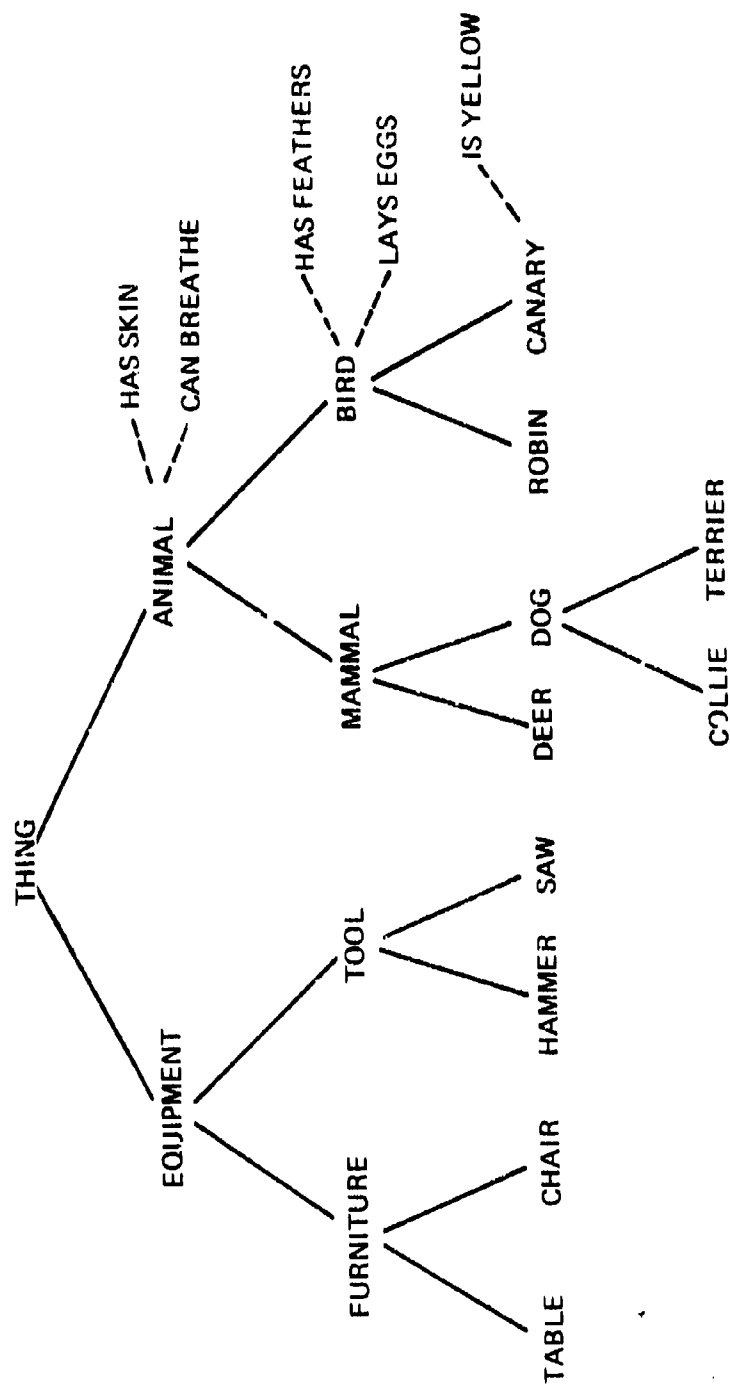


Figure 1. An example of a hierarchy of natural language concepts. Property relations are shown for ANIMAL, BIRD, and CANARY.

Subsequent research has led to some important qualifications of the original theory proposed by Collins and Quillian. Conrad (1972) showed that some of the original support for the idea of cognitive economy was due to a confounding of associative strength between nouns and properties. In particular, properties which were near to the nouns in the hierarchy tended to occur with those nouns more frequently in the language. When associative strength was controlled, there was no evidence of a hierarchical distance effect. Also, the assumption of hierarchical organization has met some difficulties. In particular, Rips, Shoben, and Smith (1973) have shown that distance in a logical hierarchy does not always predict response time. For example, people verify the sentence, "A dog is an animal" faster than the sentence, "A dog is a mammal." Smith, Shoben, and Rips (1974) discuss some of the problems associated with the hierarchy model, and they propose an alternative model using semantic features as the basic unit of analysis. Collins and Loftus (1975) present a defense of the hierarchy model. They also suggest extensions to the model which help to compensate for some of its failures.

There have been several other proposals concerning memory structures in addition to the hierarchical structure proposed by Collins and Quillian. We have already mentioned the featural analysis proposed by Smith et al. Others have proposed that a multidimensional spatial representation captures much of the organization of some conceptual domains. Shepard (1963) and Kruskal (1977) have investigated the applicability of multidimensional spatial representations for a number of conceptual domains with some encouraging results. It can be difficult to discover the identity of the underlying dimensions which limits the value of the analysis in some cases. However, multidimensional scaling (MDS) does provide a metric (distance in multidimensional space) which can be valuable. The present project has investigated memory structure using the spatial methods developed by Shepard and Kruskal.

There have also been proposals that constitute generalizations of the hierarchical model proposed by Collins and Quillian. One such model, proposed by Collins and Loftus (1975), assumes that concepts are organized as nodes in a network but the organization of the network is not necessarily hierarchical. Retrieving information from such a network requires the "activation" of particular nodes.

A powerful context mechanism in models of memory structure is termed "spreading activation" (Collins & Quillian, 1969; Collins & Loftus, 1975; Meyer & Schvaneveldt, 1971, 1976; Schvaneveldt & Meyer, 1973; Schvaneveldt, Durso, & Mukherji, 1982). According to spreading activation theory, the activation of a node in the network leads to a spread of activation to other, nearby, nodes. Because of the organization of the network, the nearby nodes are semantically related. Thus, spreading activation makes related concepts more readily accessible once a particular concept has been activated.

While much of the theory concerning structure and process in semantic memory has been based on network structures, there have been no empirical methods available to generate networks from data. One major accomplishment of the present project has been the development of such a method. The general weighted network (GWN) algorithm uses the same data as other methods. Thus, the various structural representations can be compared using the same data sets.

Development of Conceptual Structures

One approach to the validation of conceptual structures involves demonstrating an orderly development of the structures in student pilots as they gain more experience. The structures derived from the student data will be compared with those derived from instructors to identify aspects of the conceptual structure which undergo marked changes with training and aspects that remain relatively stable.

During the past year, we have investigated the development of spatial representations and of networks of concepts. Of interest is the extent to which students can be distinguished from instructors on the basis of their conceptual structures. We have also attempted to identify specific concepts and relations between concepts which distinguish instructors from students.

In summary, the present investigation employs several methods that produce structural descriptions for concepts from split-plane maneuvers (Table 1) and from the low-angle strafe (Table 2). We have derived multidimensional spatial representations, cluster analyses (Johnson, 1967), and network representations for these maneuvers. Multidimensional spatial representations show the location of each concept in a multidimensional psychological space where the Euclidean distance between concepts represents psychological proximity. Cluster analyses produce a series of groupings of concepts, reflecting underlying psychological categories of concepts. Cluster analyses impose a hierarchical constraint on the groupings such that smaller groups form a subset of larger groups. In a network representation, each concept occurs as a node in a network, and psychological distance is represented by the distance between nodes. Network representations can reveal several different kinds of organizations including hierarchies, cycles, and chains of concepts. The validity of these representations is assessed by various criteria, including consistency within and between individuals, the development of the representations with training and experience, and performance in speeded identification tasks.

GENERATION OF STIMULUS MATERIALS

A review of training and technical order publications related to tactical flight operations and tactical aircraft provided a potential set of stimulus items. One member of the research team was familiar with tactical flight operations as an Air Force navigator, and he was responsible for the generation of preliminary stimulus sets related to critical flight information and aircraft systems.

Early in this phase of research, a recent AFHRL technical report came to our attention. The report (Meyer, Laveson, Pape, & Edwards, 1978) included the identification and detailed task analyses of selected basic tactical flight maneuvers. Of particular interest were the following:

1. The breakdown of tactical operations into two practical categories, air-to-air and air-to-ground.
2. Results of analyses which identified "highly representative" maneuvers from each of the above categories.
3. The use of a scenario as a means of collecting data from experienced aircrew members.

Based on the Meyer et al. report, two representative maneuvers were selected for further investigation. The two maneuvers, low yo yo and low-angle strafe, representing air-to-air and air-to-ground categories, respectively, together with a general list of tactical aircraft systems, were selected for further stimulus generation and validation efforts.

Interviews were conducted with four instructor pilots from Holloman AFB. The interviews were conducted informally and involved examination of general concepts related to air-to-air versus air-to-ground operations depending on the specialties declared by the interviewees. Conceptual units, words and phrases, were then compiled into preliminary stimulus lists. Detailed review of the Meyer et al. task analyses provided additional stimulus items and a basis for eliminating items not directly related to the target maneuvers selected for further study.

It became apparent that within each selected maneuver, certain items on the list could be considered assumptions necessary to limit the scenario to a particular maneuver. Certain others were essential or central to the maneuver, and, still others, to varying degrees, were only "related" to the maneuver in a more abstract sense. Accordingly, the preliminary lists were broken down into three subsets based on best available information. These lists, together with an outline of aircraft systems, were then ready for validation.

The validation process consisted of a series of interviews with individual tactical fighter pilots on a series of visits to Holloman AFB. The purposes of the project were explained to each pilot who was then asked to review a list of concepts. The resulting additions, deletions, and shifts (e.g. from "related" to "essential" subsets) were iteratively incorporated in succeeding interviews. The 10 interviews conducted in this phase resulted in the following:

1. The low yo yo scenario was expanded to include all primary split-plane maneuvers. Pilot experts made it clear that, even with multiple scenario-related restrictions, a real world situation could precipitate any combination of split-plane maneuvers and no single set of restrictions would evolve into a low yo yo maneuver exclusively. Since many of the essential concepts established in the list were common to all split-plane maneuvers, only minor expansion of the stimulus set was required.

2. The low angle strafe maneuver was kept limited in scope and could be effectively restricted to the specified maneuver given few scenario-related assumptions.

3. The aircraft systems list was trimmed considerably. Pilots indicated that, while all represented subsystems could be considered critical in some sense, knowledge about several aircraft systems only became critical when specific malfunctions occurred in flight.

4. The "basic concepts" subset of each maneuver was refined to include 30 items consistent with practical experimental manipulation in the next phases of the project.

5. The "assumptions" subset of each list was restricted to less than 10 items to provide a manageable scenario description during the next phases of data collection.

The resulting lists of stimulus items are shown in Tables 1, 2, and 3.

Table 1. SCENARIO: SPLIT-PLANE MANEUVERS

Assumptions

OFFENSIVE	AGGRESSIVE	TALLY HO
SINGLE BANDIT	KILL	EQUAL OR SIMILAR AIRCRAFT
COMMIT	ENGAGED	IR MISSILE PARAMETERS
DEFENSIVE TURN (TARGET DENIES MISSILE)		

Basic Concepts

LOW YO YO	HIGH YO YO	QUARTER PLANE
LAG ROLL	BARREL ROLL	OVERTAKE
GUNS	AIRSPEED	ANGLE OFF
G LOADING	CUTOFF	RELATIVE ENERGY
6 O'CLOCK	SMASH	POWER SETTING
SWITCHOLOGY	ACCELERATION	RADIAL G
HEAT	SNAPSHOT	VERTICAL MANEUVERING
3-9 LINE	EXTENSION	WEAPONS PARAMETERS
LAG PURSUIT	LIFT VECTOR	CORNER VELOCITY
ASPECT ANGLE	PURE PURSUIT	LEAD PURSUIT

Other Related Concepts

THREAT	DISENGAGE	BINGO
JOKER	SADDLED-UP	LOW PK
HIGH PK	BURIED NOSE	REVERSAL
SHOOTER	LOAD	PADLOCK
RTB	EGG	OP TURN
MAX TURN	TRAPPED NOSE	LINE OF SIGHT RATE
NOSE COUNTER	KNOCK-IT-OFF	OVER PULL
UNDER PULL	SEPARATE	SUN
CLOUDS		

Table 2. SCENARIO: LOW ANGLE STRAFE

Assumptions

CONTROLLED RANGE CLEARED	PANEL/TARGET SWITCHOLOGY	TARGET ACQUISITION
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Basic Concepts

DRIFT	AIM OFF POINT	DIVE ANGLE
GLIDE PATH	FOUL LINE	CLOSURE
AIRSPPEED	RUN-IN LINE	ALTITUDE
BANK	PIPPER FIXATION	WALKING
TRIGGER	TRACKING	PULL UP
RICOCHET	YAW	FINAL
BURST	RECOVERY	BUNT
STABILIZE	TRIM	FOUL
RANGE	PIPPER PLACEMENT	FIRE
BULLET IMPACT	GUNS	AIM POINT

Other Related Concepts

RETICLE	CROSSWIND LEG	ROLL IN
ANGLE OF ATTACK	MIL CRANKING	DOWNWIND LEG
BASE LEG	WIRE	PRESS
SIGHT PICTURE	TRACER	SPACING
WINDS	REJOIN	BEARING
AZIMUTH	LAZY PULL	TOWER
DOWN-THE-CHUTE	DISPERSION	COFFIN CORNER
DOUBLE BURST	PENDULUM EFFECT	EJECTION
ROLLING PULL	LONG BURST	

Table 3. ESSENTIAL AIRCRAFT TERMS

FLIGHT-CONTROL SYSTEM	STICK
PITCH DAMPER SWITCH	FLIGHT-TRIM SWITCH
ADI	ALTIMETER
CAS/MACH	RUDDER PEDALS
RUDDER TRIM KNOB	YAW DAMPER SWITCH
THROTTLES	FUEL-QUANTITY INDICATORS
FUEL-FLOW INDICATORS	NAVIGATION SYSTEM
COMM RADIO	FIRE-CONTROL SYSTEM
RADAR MISSILE	MISSILE COMPUTER
GUN COMPUTER	OPS CHECKS
HUD	CANOPY
EJECTION SYSTEM	UHF

SIMILARITY-RELATEDNESS RATINGS

Method

Most scaling procedures for producing structural descriptions of a set of concepts require some measure of psychological distance between the concepts. Accordingly, we developed a similarity or relatedness rating procedure which provided measures of similarity between the members of all possible pairs of the basic concepts from the two selected scenarios (see Tables 1 and 2).

A program was developed for the TERA microcomputer to collect the rating data. The intent was to produce a program that would essentially allow subjects to perform the task without outside assistance. Since tests were to be conducted during normal duty hours, the aim was to establish a method for collecting data that would impinge on subjects' time as little as possible. Since the TERA could be continually available at Holloman AFB, subjects were able to run through our programs whenever they had a few minutes of free time. The TERA was programmed to automatically start the program whenever it was turned on. Posters were prepared with detailed instructions about starting the TERA.

Once started, the TERA presented instructions for the task on its video display. The instructions described the nature of similarity or relatedness ratings and gave the details on entering the ratings into the computer. A scenario was described to provide a context for rating the terms, and the complete set of terms to be rated was shown to allow subjects to establish some criteria for rating the pairs of concepts. The rating task itself consisted of presenting all possible pairs of the 30 basic concepts from one of the sets of terms. Thus subjects rated the similarity of 435 pairs of terms during the session. For each pair of terms, the TERA displayed the pair of terms to be rated, a rating scale with the numbers 0 through 9, and a bar marker to indicate the rating. Subjects entered their rating by pressing a number key on the TERA keyboard. The bar marker in the display was moved to the position corresponding to the number entered by the subject to indicate the rating given. Subjects could change the rating by pressing another number key, and the bar marker would move to the position corresponding to the new number. When satisfied with the rating, the subject pressed the SPACE BAR on the keyboard, and the display changed to show the next pair of items and to reset the bar marker to the bottom of the scale. This procedure was followed until all 435 pairs had been presented. The order of the pairs was independently randomized for each subject. A rating session required from 30 to 45 minutes to complete, and the TERA then presented a debriefing to the subject explaining the purpose of the research.

Table 4 summarizes the subject groups that were tested with the rating task. Table 5 shows the flying time for each subject.

Table 4. Summary of Subject Groups for the Rating Task

<u>Group</u>	<u>n</u>	<u>Description</u>	<u>Location</u>
<u>Split-plane Maneuvers</u>			
IP	7	Instructor Pilots	Holloman AFB
GP	9	Air National Guard Pilots	Buckley ANGB
UP	17	Undergraduate Pilots (UPTs)	Williams AFB
IW	4	Instructor Weapons Systems Officers	Holloman & Williams
<u>Low Angle Strafe Maneuver</u>			
IP	6	Instructor Pilots	Holloman AFB
UP	16	Undergraduate Pilots (UPTs)	Williams AFB
IW	7	Instructor Weapons Systems Officers	Holloman & Williams

Table 5. Hours of Flying Time for Each Subject

Subject Number	Split-Plane Maneuvers				Low Angle Strafe		
	IP(I)	GP(G)	UP(U)	IW(W)	IP(I)	UP(U)	IW(W)
1	2850	3221	182	800	2850	200	800
2	4300	3500	200	950	4300	105	970
3	3300	2100	105	725	1850	200	1500
4	2300	21000	200	3000	1400	188	1100
5	1230	3850	188		4400	175	2100
6	1600	10650	175		2600	200	725
7	4400	4000	200			180	3000
8		4000	180			206	
9		2256	206			250	
10			250			200	
11			200			196	
12			196			300	
13			300			175	
14			175			173	
15			173			200	
16			200			275	
17			275				

Note. IP - Instructor Pilots

GP - Air National Guard Pilots

UP - Undergraduate Pilots (UPTs)

IW - Instructor Weapons Systems Officers

The letters shown in parentheses next to the group labels are used to designate particular individuals in the group, e.g., I1 represents the first IP listed.

The portability of the research apparatus permitted collection of data at several geographically separated locations by different researchers. National Guard pilots were tested at the Buckley unit of the Air National Guard. Instructor pilots and weapons systems officers were tested at Holloman AFB. Undergraduate Pilot Training subjects and some weapons systems officers were tested at Williams AFB.

The obtained similarity measures were transformed into measures of psychological distance by subtracting the ratings from the maximum possible rating. The resulting numbers reflect distance with the larger numbers representing greater psychological distance between concepts.

The rating task provided the data base for much of the work described in this report. In particular, the ratings were used to evaluate consistency within and between individuals and within and between groups. The ratings were also used to produce multidimensional scaling solutions, hierarchical clusters, networks, and classification algorithms. The details for each structural analysis are presented in the appropriate sections.

Since some of the subjects tested were in UPT training, it was desirable to determine how familiar they were with the concepts from the two lists. Accordingly, the UPT subjects rated their familiarity with the terms on a three point scale. A rating of 1 indicated that they had no familiarity at all with the concept. A rating of 2 indicated that they were familiar with the term but did not use it in flying. A rating of 3 indicated that the term was used in flying. Summaries of the familiarity rating data are shown in Tables 6 and 7. Table 6 shows the familiarity of each of the concepts to the group of UPTs as a whole. Table 7 shows the familiarity indicated by each of the UPTs for the set of concepts as a whole.

As can be seen from the tables, the UPTs show a reasonable degree of familiarity with the concepts. Overall, 65% of the responses indicate at least some familiarity with the split-plane concepts, and 73% of the responses indicate at least some familiarity with the low-angle strafe concepts. Obviously, students are not as familiar with the concepts as instructors (who selected the concepts to begin with). There are a few concepts which are not very familiar, but overall the students appear to know, or at least know about, most of the concepts. Also, the later analyses suggest that there are systematic differences between UPTs and other groups which are more likely based on systematic misunderstanding of the concepts by the UPTs rather than a lack of familiarity. The fact that some of the analyses show differences between Air National Guard Pilots and Instructor Pilots suggests that the ability to discriminate between groups is not solely based on a lack of familiarity in one of the groups.

Table 6. Familiarity of UPTs with Individual Concepts

Split-Plane Maneuvers				Low-Angle Strafe			
Familiarity Rating				Familiarity Rating			
Concept	1	2	3	Concept	1	2	3
LOW YO YO	10	6	0	DRIFT	0	6	9
HIGH YO YO	8	8	0	AIM OFF POINT	12	2	1
QUARTER PLANE	14	2	0	DIVE ANGLE	1	9	5
LAG ROLL	13	3	0	GLIDE PATH	0	3	12
BARREL ROLL	0	1	15	FOUL LINE	14	1	0
OVERTAKE	0	0	16	CLOSURE	0	5	10
GUNS	1	14	1	AIRSPPEED	0	2	13
AIRSPPEED	0	0	16	RUN-IN-LINE	14	1	0
ANGLE OFF	4	8	4	ALTITUDE	0	1	14
G LOADING	0	1	15	BANK	0	1	14
CUTOFF	0	0	16	PIPPER FIXATION	7	8	0
RELATIVE ENERGY	0	4	12	WALKING	12	3	0
6 O'CLOCK	0	3	13	TRIGGER	2	13	0
POWER SETTING	0	0	16	TRACKING	1	10	4
SWITCHOLOGY	7	5	4	PULL-UP	3	5	7
ACCELERATION	0	1	15	RICOCHET	6	9	0
RADIAL G	12	3	1	YAW	0	2	13
SMASH	1	1	14	FINAL	2	4	9
HEAT	13	3	0	BURST	3	12	0
SNAPSHOT	13	3	0	RECOVERY	1	8	6
VERTICAL MANEUVER	0	2	14	BUNT	14	1	0
3-9 LINE	12	4	0	STABILIZE	2	6	7
WEAPONS PARAMS	4	12	0	TRIM	0	1	14
CORNER VELOCITY	1	8	7	FOUL	14	1	0
LIFT VECTOR	0	4	12	RANGE	1	12	2
EXTENSION	13	3	0	PIPPER PLACEMENT	6	9	0
ASPECT ANGLE	13	3	0	FIRE	1	14	0
LAG PURSUIT	10	4	2	BULLET IMPACT	3	12	0
PURE PURSUIT	9	5	2	GUNS	1	14	0
LEAD PURSUIT	10	4	2	AIM POINT	1	7	7
Total	168	115	197		121	182	147
Percent	35	24	41		27	40	33

Note. Entries in the table are the number of UPTs giving each rating to each concept.

1-Totally Unfamiliar

2-Familiar but not used in flying

3-Used in flying

Table 7. Familiarity of Individual UPTs with All Concepts

Split-Plane Maneuvers				Low-Angle Strafe		

Familiarity Ratings						
UPT	1	2	3	1	2	3
U1	6	10	14	9	13	8
U2	12	6	12	8	13	9
U3	12	6	12	19	3	8
U4	15	3	12	4	10	16
U5	12	5	13	6	14	10
U6	4	11	15	6	16	8
U7	7	7	16	6	13	11
U8	10	8	12	6	10	14
U9	13	4	13	-	-	-
U10	-	-	-	7	12	11
U11	7	13	10	9	10	11
U12	14	10	6	8	11	11
U13	9	9	12	8	11	11
U14	15	3	12	11	8	11
U15	11	6	13	5	25	0
U16	5	8	17	7	12	11
U17	14	6	10			

Note. Entries in the table are the number of concepts given each rating by each UPT.
 1-Totally Unfamiliar
 2-Familiar but not used in flying
 3-Used in flying

Results and Discussion

The first step toward establishing the validity of the rating data requires determining the extent to which different subjects agree about the ratings. Under the assumption that the cognitive structures underlying the ratings are shared by people with similar experiences, agreement in the ratings presumably reflects the shared structures. Table 8 shows the correlations between the ratings given by each pair of instructor pilots. Instructor pilots were chosen for this test since they presumably have an organization of the concepts which is communicated to the students they are training. In other words, instructors can be expected to have a reasonably well defined structure. Correlating the ratings they give to the various pairs of concepts should reflect the extent to which they share a common structure, as well as the extent to which the ratings succeed in capturing that common structure.

The correlations between members of a pair of individuals average about .43 (the average of the off-diagonal entries). Given the large number of pairs on which these correlations are based, they are all statistically significant (Critical values of r are approximately .10 for the .05 level of significance and .13 for the .01 level of significance). The obtained correlations suggest a moderate amount of agreement among the instructor pilots in the ratings assigned to the 435 pairs of basic concepts in each set of material.

The values on the main diagonals (underlined) in the matrices in Table 8 show reliability estimates from pilots who were retested after an interval of 6 to 8 months. With an interval that long between the original test and the retest, the second set of ratings presumably reflects the individual's cognitive structure rather than memory for the ratings given on the initial test. The reliability coefficients average about .62 which indicates that approximately 38% of the variance in the ratings is stable over time within an individual. The average correlation between individuals of .43 leads to the conclusion that agreement between individuals accounts for about 18% of the variance in the ratings. Putting these two facts together leads to the conclusion that individuals share about 47% of the consistent variance in the ratings ($18\%/38\%$). These values suggest that the agreement between individuals is not only statistically significant, but is sufficiently large to be of practical significance as well. For present purposes, the rating data have sufficient reliability and the agreement between individuals is sufficiently high to allow further structural analyses of these data.

Table 8

Inter-Individual Correlation Matrix on Rating Scores

I1 through I7 are individual instructor pilots

Split-Plane Maneuvers

	I1	I2	I3	I4	I5	I6	I7
I1	-	.35	.47	.45	.42	.58	.43
I2	.35	-	.41	.41	.47	.38	.32
I3	.47	.41	-	.49	.43	.42	.43
I4	.45	.41	.49	-	.41	.43	.41
I5	.42	.47	.43	.41	-	.42	.41
I6	.58	.38	.42	.43	.42	-	.37
I7	.43	.32	.43	.41	.41	.37	<u>.67</u>

Low-Angle Strafe Maneuver

	I1	I2	I3	I4	I5	I6
I1	-	.49	.39	.57	.49	.41
I2	.49	-	.40	.50	.42	.39
I3	.39	.40	<u>.54</u>	.47	.36	.31
I4	.57	.50	.47	-	.53	.45
I5	.49	.42	.36	.53	<u>.71</u>	.42
I6	.41	.39	.31	.45	.42	<u>.54</u>

HIERARCHICAL CLUSTERING

Figures 2 through 5 show the results of a hierarchical clustering analysis of the basic concepts from the two sets of concepts. Figure 2 shows the groupings of concepts for the split plane maneuvers for the instructor pilots, and Figure 3 shows the same analysis for the undergraduate pilots. The clusters found in the data from the split-plane concepts for both instructor pilots and undergraduate pilots are shown in Table 9. In several of the methods used to compare students and instructors, there are areas of agreement and disagreement in the conceptual structures. For example, instructors and students agree about the grouping of the concepts GUNS and SNAPSHOT. However, students group HI YO YO with LO YO YO, and the instructors do not make such a grouping. Perusal of Table 9 will reveal several other examples.

Similar analysis of the data from the concepts related to the low-angle strafe are shown in the next two figures. Figure 4 shows the groupings of the concepts for the instructor pilots, and Figure 5 shows the results for the undergraduate pilots.

In general, the hierarchical clustering analysis yields sensible groupings of the concepts, especially for the instructor pilots. These results generally confirm the validity of the procedures we have used. The cluster analysis does not readily yield information permitting more detailed analysis than the concept clusters themselves. The multidimensional scaling procedure and the network analysis have proven to be more useful in pushing the analysis of the differences between students and instructors to a more detailed level. Next, we turn to those analyses.

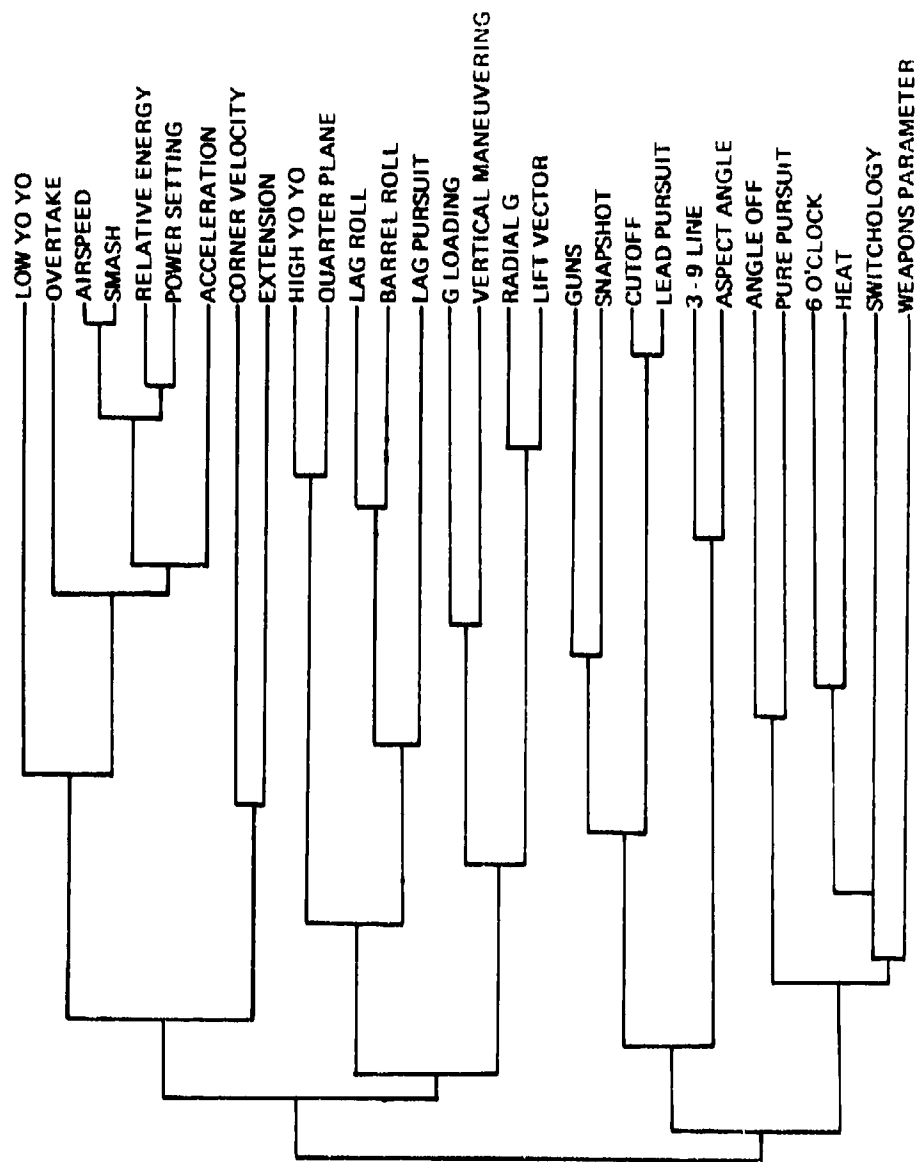


Figure 2. Results of Hierarchical Clustering Analysis of Split Plane concepts for Instructor Pilots.

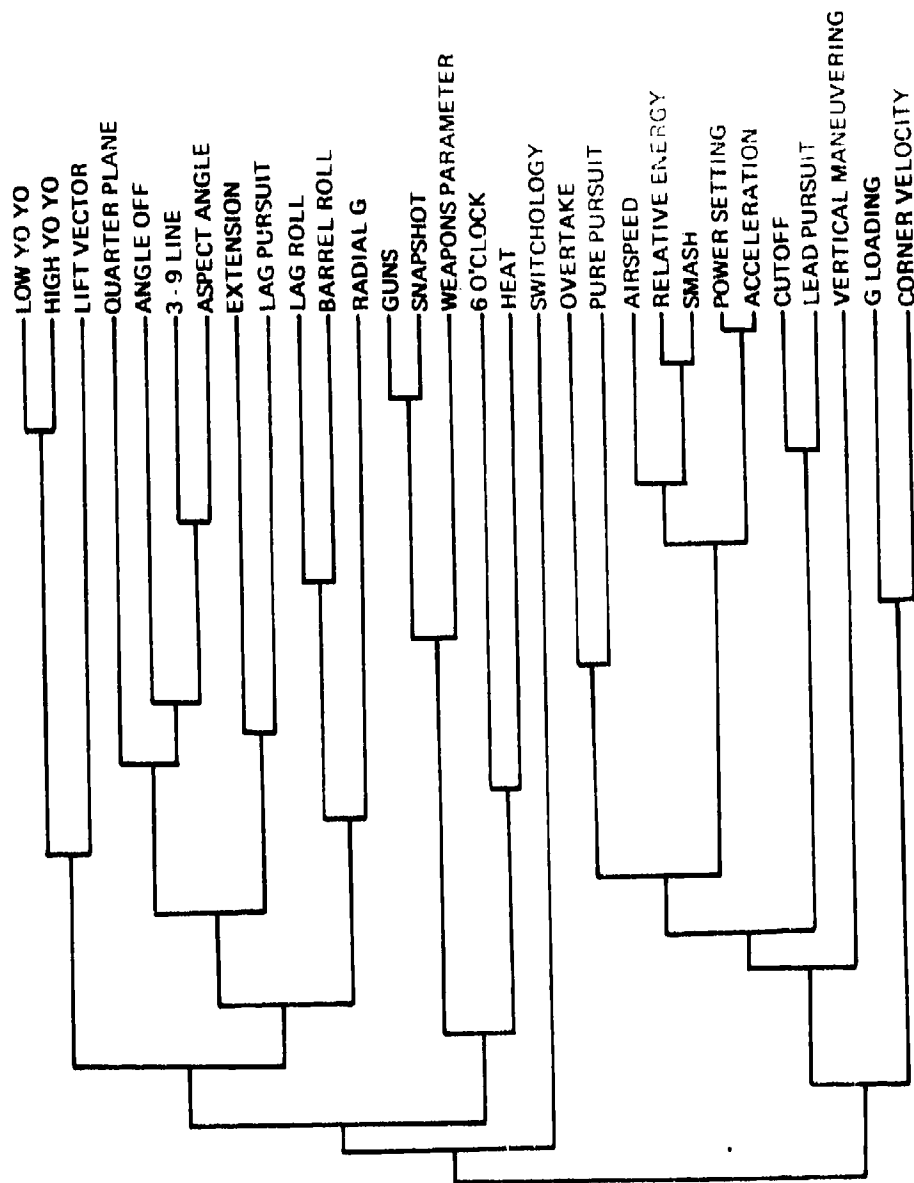


Figure 3. Results of Hierarchical Clustering Analysis of Split Plane concepts for Undergraduate Pilot Trainees.

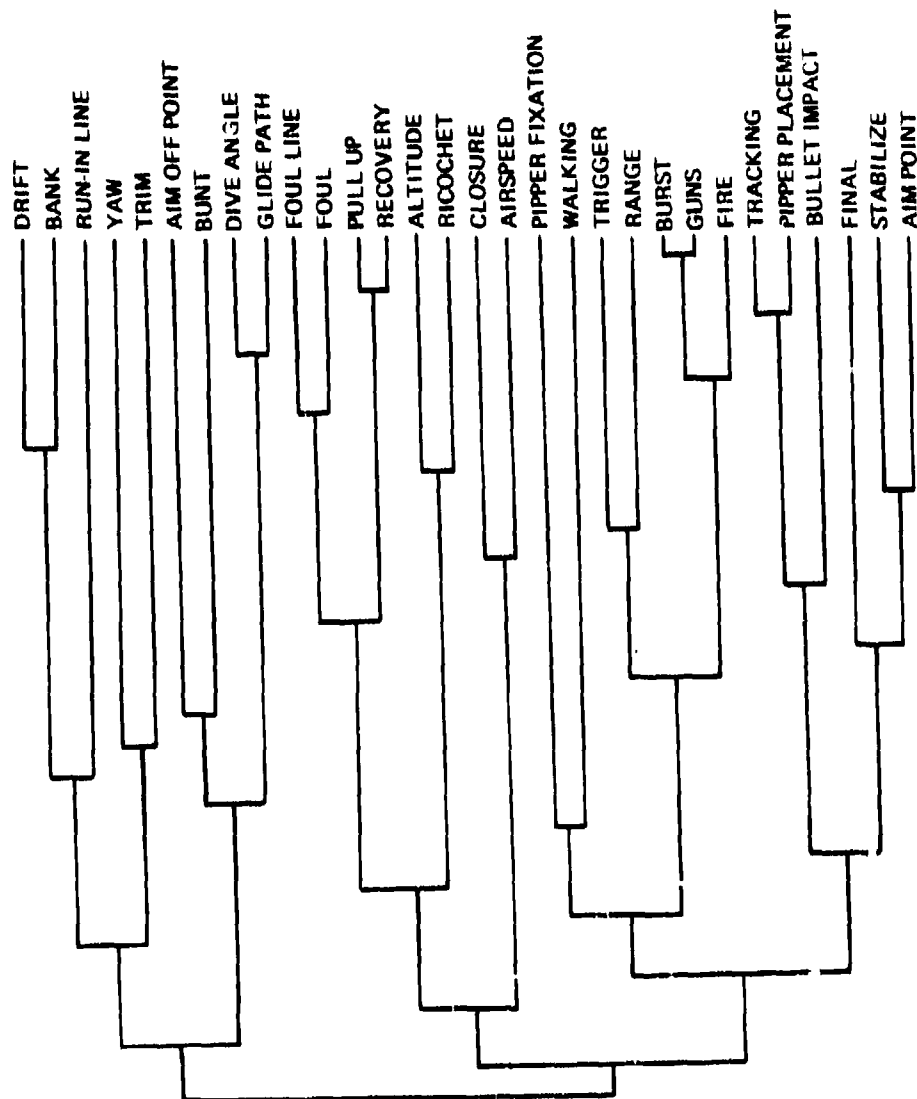


Figure 4. Results of Hierarchical Clustering Analysis of Srafe concepts for Instructor Pilots.

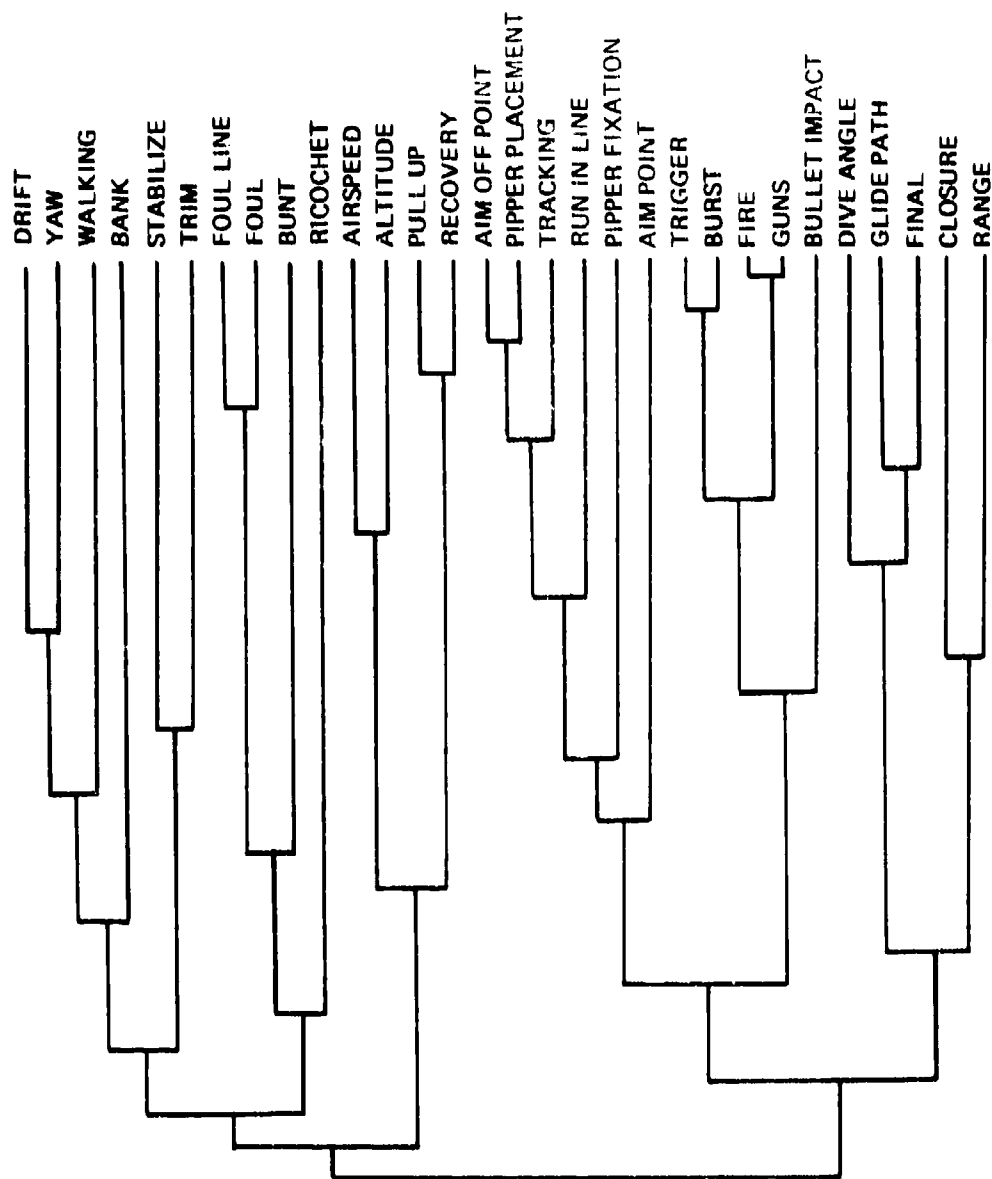


Figure 5. Results of Hierarchical Clustering Analysis of Strafe concepts for Undergraduate Pilot Trainees.

Table 9. Major Clusters of Split-Plane Concepts

Group 1	Group 2	Group 3	Group 4	Group 5
Instructor Pilots				
LO YO YO	HI YO YO	G LOADING	GUNS	ANGLE OFF
OVERTAKE	QTR PLANE	VERT MANEUV	SNAPSHOT	PURE PURSUIT
AIRSPEED	LAG ROLL	RADIAL G	CUTOFF	6 O'CLOCK
SMASH	BARREL ROLL	LIFT VECTOR	LEAD PUR	HEAT
REL ENERGY	LAG PURSUIT		3-9 LINE	SWITCHOLOGY
PWR SETTING			ASPECT ANGL	WEAPNS PARMS
ACCEL				
CORNER VEL				
EXTENSION				
Undergraduate Pilots				
LO YO YO	GUNS	SWITCHOLOGY	OVERTAKE	G LOADING
HI YO YO	SNAPSHOT		PURE PUR	CORNER VEL
LIFT VECTOR	WEAPNS PARMS		AIRSPEED	
QTR PLANE	6 O'CLOCK		REL ENERGY	
ANGLE OFF	HEAT		SMASH	
3-9 LINE			PWR SETTING	
ASPECT ANGL			ACCEL	
EXTENSION			CUTOFF	
LAG PURSUIT			LEAD PUR	
LAG ROLL			VERT MANEUV	
BARREL ROLL				
RADIAL G				

MULTIDIMENSIONAL SCALING

Structures. The results of two-dimensional scaling solutions are shown in Figures 6 through 9. Figure 6 shows the spatial layout of the concepts for IPs for concepts from split-plane maneuvers. Figure 7 shows the layout generated for the undergraduate pilots for the same set of concepts. The spatial layouts for the low-angle strafe concepts are shown in Figures 8 and 9 for the instructor pilots and the undergraduate pilots, respectively. In these figures, the position of the concept is what is being represented. The horizontal position represents the location of the concept on one dimension, and the vertical position represents the location of the concept on a second dimension.

Since the figures only represent the two-dimensional scaling solutions, they do not capture the complete structures since more dimensions are required to represent the total complexity of these sets of concepts. Unfortunately, solutions with more than two dimensions are difficult to represent. However, the two-dimensional representations in the figures do reveal some interesting aspects of the conceptual structures. Comparing the instructors with the undergraduates (Figures 6 and 7), for example, reveals some similarities in the relative locations of the concepts SWITCHOLOGY, HEAT, GUNS, and WEAPONS PARAMETERS in the two structures. There are clear differences in the relative locations of other concepts. Students have HI YO YO and LO YO YO located near one another while these two concepts are much further apart in the structure developed from the instructor data. We will return to a detailed analysis of the differences between experienced and inexperienced pilots in some of the later analyses.

The structures we used for further analyses were based on five dimensions for the split-plane maneuvers and four dimensions for the low-angle strafe. The dimensionality of each set was chosen by plotting the variance in the instructor data which is accounted for by the variance in the instructor structures. The point at which the function began to level off was selected as the appropriate dimensionality for that set of concepts. Interestingly, this procedure leads to a more complex structure for the split-plane maneuvers than for the low-angle strafe. Such a difference would be expected on the basis of the difference in complexity for the two sets of concepts.

Multidimensional scaling solutions have two properties that are of considerable interest. First, they provide a dimensional organization that can reveal interesting global structures in the data. Second, they yield a metric (distance between concepts in multidimensional space) which has some useful applications. Next, we turn to a discussion of these properties in the data from the instructor pilots.

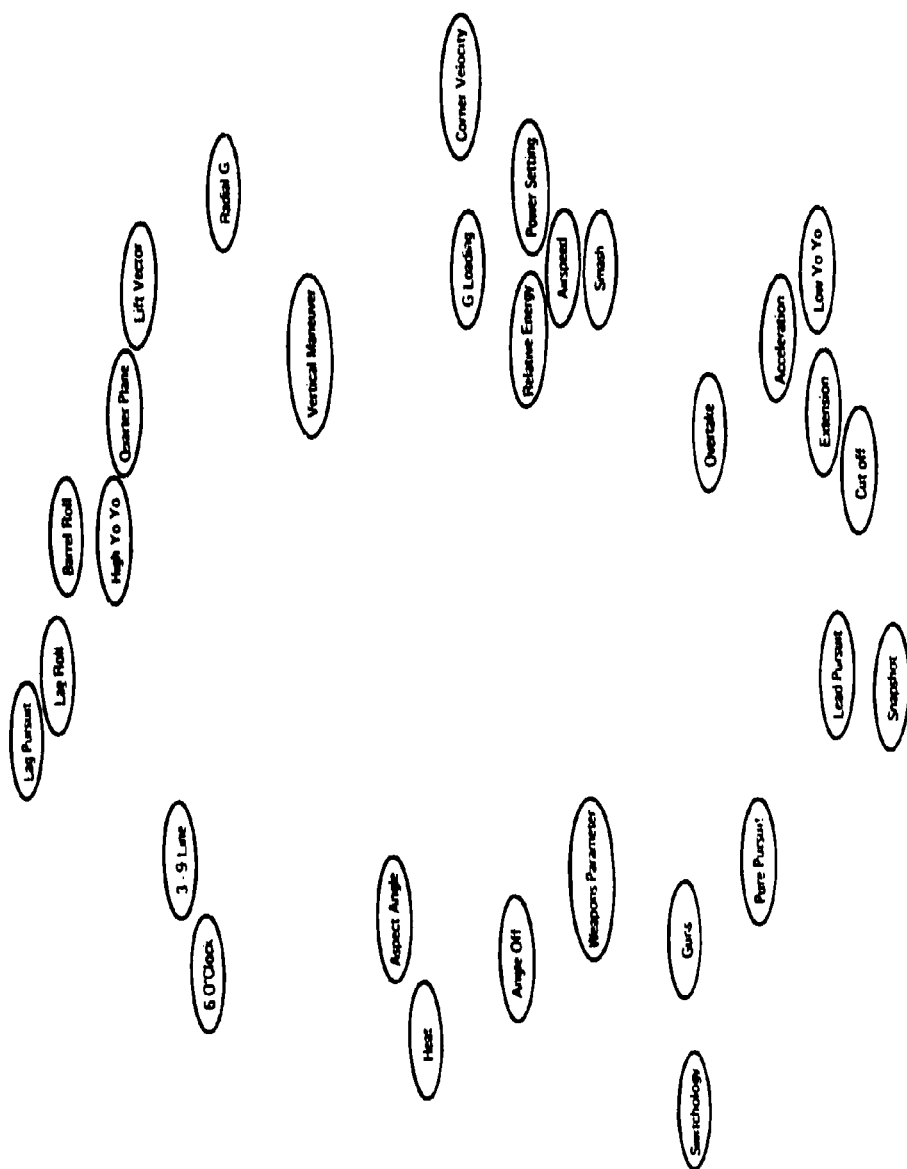


Figure 6. Multidimensional Scaling solution of Split Plane concepts for instructor Pilots.

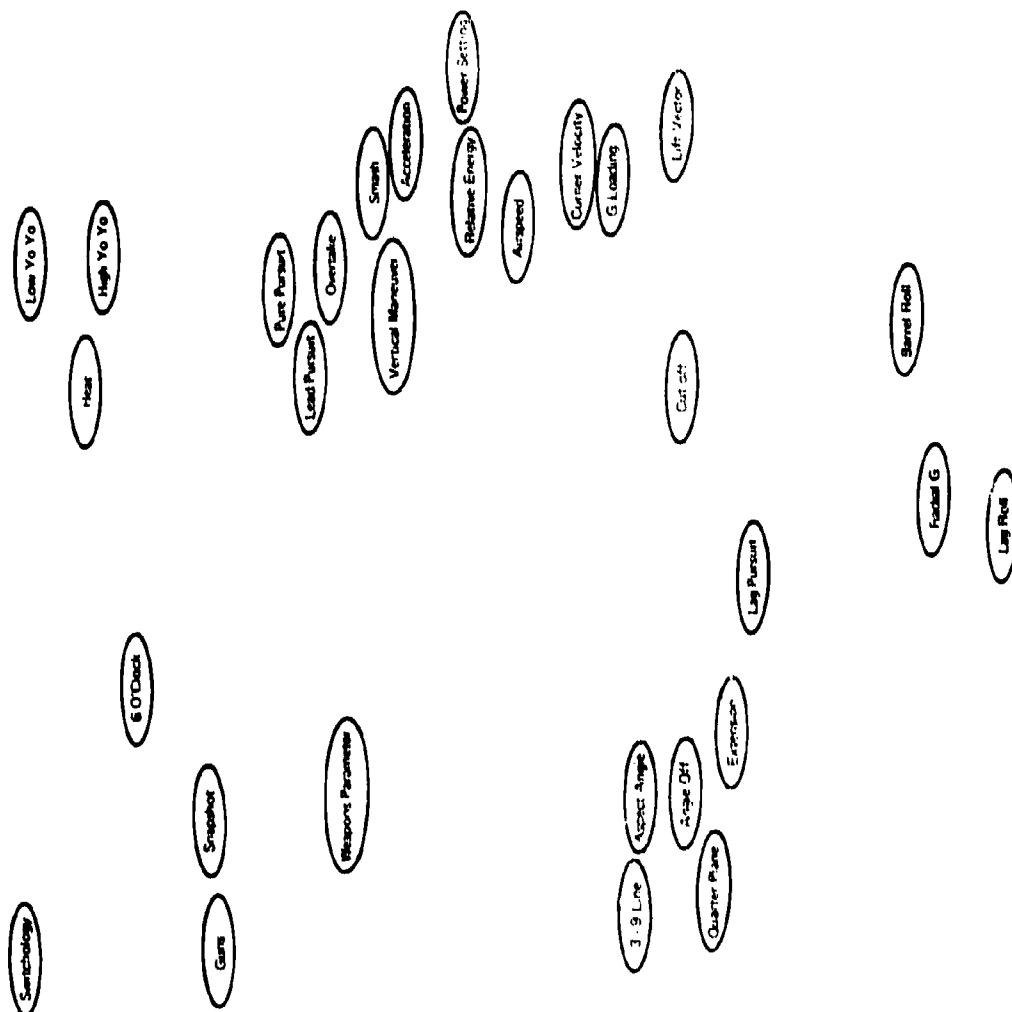


Figure 7. Multidimensional Scaling solution of Split Plane concept for Undergraduate Pilot Trainees.

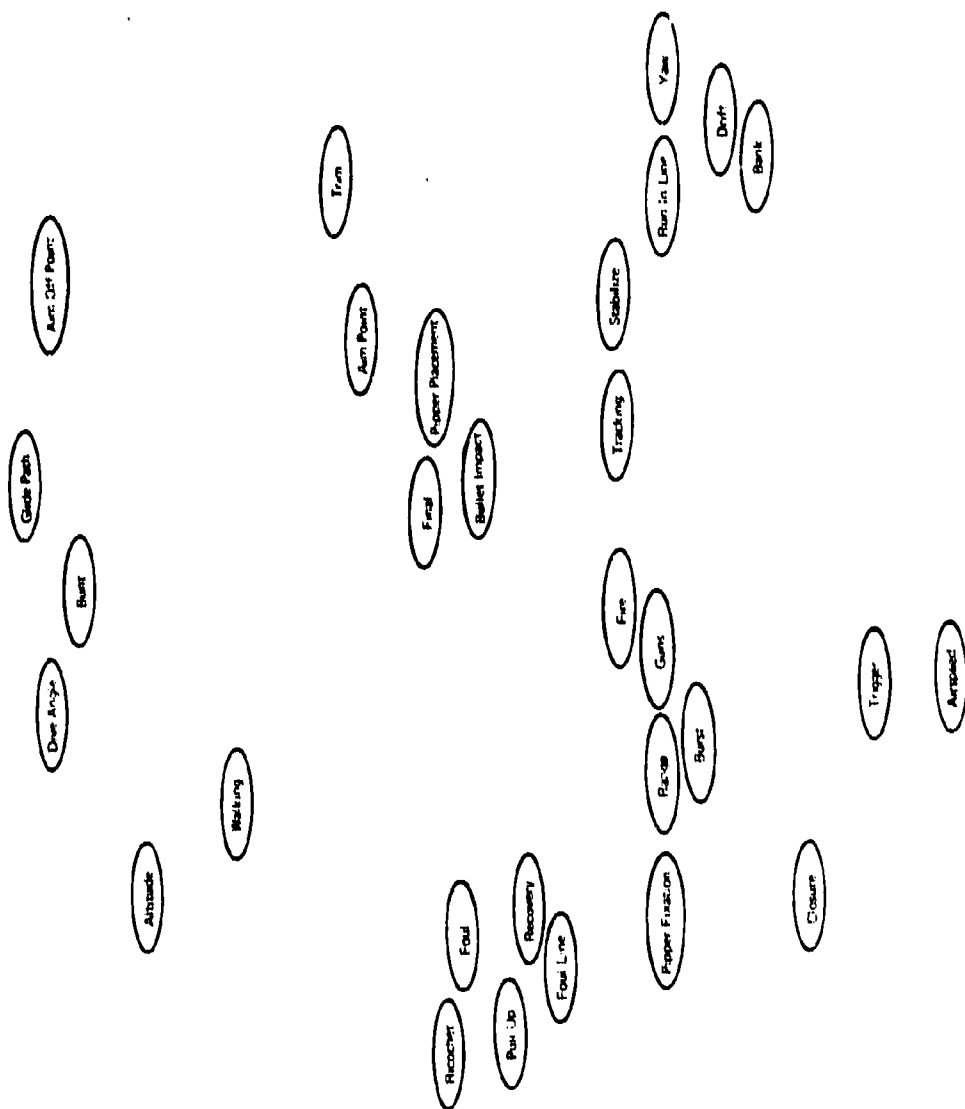


Figure 8. Multidimensional Scaling solution of Sirafe concepts for Instructor Pilots.

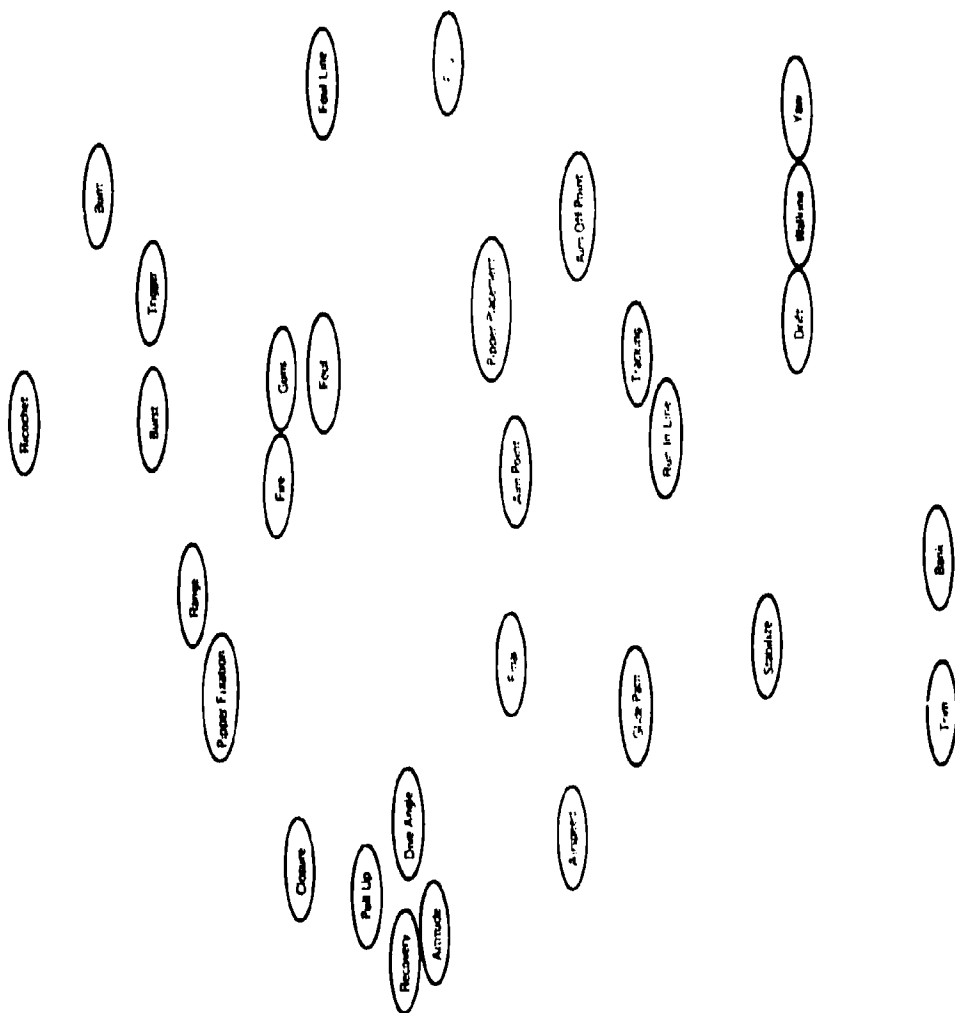


Figure 9. Multidimensional Scaling solution of Srafe concepts for Undergraduate Pilot Trainers.

Dimensions in Multidimensional Space. Some of the major dimensions have been identified for the spatial layout of the concepts for instructors. The split-plane concepts have two dimensions associated with temporal factors and one dimension which distinguishes particular maneuvers. The first temporal dimension identifies the general time dimension within a scenario leading to split-plane maneuvers. In Figure 6, this dimension is the main horizontal dimension ordered from left to right. The concepts on the extreme left (SWITCHOLOGY, HEAT, and ANGLE OFF) refer to events or considerations that occur early in the temporal sequence. Moving to the right, we encounter concepts referring to events and considerations occurring later in the sequence. The second temporal dimension represents the ordering of concepts in a standard training sequence which instructors and students frequently follow in practicing the maneuvers. This dimension occurs as the third dimension in the solution and is not shown in Figure 6. The vertical dimension in Figure 6 has been identified as a contrast between lead pursuit and lag pursuit with lag pursuit and the associated maneuvers near the top and lead pursuit and LOW YO YO near the bottom.

The low angle strafe maneuver also provided a temporal order dimension as the first dimension in the solution. Again, this dimension occurs as the first dimension in the solution, and it reflects the order in which the concepts would occur to pilots in executing the low angle strafe. Interestingly, this dimension appears to reflect the psychological ordering of the concepts rather than the order in which the events occur in physical time. Apparently, pilots must consider several factors early in time, before they actually occur, in order to be able to concentrate on critical factors such as aiming and firing. The MDS dimension appears to reflect this order of consideration. This dimension appears as the horizontal dimension in Figure 8 where the ordering of the concepts in time occurs from right to left.

These dimensions are summarized in Table 10. Apparently the temporal order dimension is a powerful one in the organization of these concepts for pilots. This dimension shows up consistently. The dimensional organization of the concepts is interesting, and it lends some support to the validity of the analytic procedures underlying the MDS solutions. However, the conclusions drawn so far are rather general and of limited utility. More fine-grained analyses of the structures are required to lead to conclusions that may be usefully applied. The metric-based analyses will take us a step in the direction of applicable findings.

Table 10. Identity of the Dimensions in Multidimensional Space

<u>Dimension</u>	<u>Identity</u>	<u>Concept Set</u>
1	Temporal Order of Consideration	Split-plane
2	Lead versus Lag Pursuit	Split-plane
3	Events in a Training Sequence	Split-plane
1	Temporal Order of Consideration	Low Angle Strafe

The MDS Metric. Table 11 shows the average correlations on the split-plane concepts both between people in the same group and between individuals in different groups. Table 12 shows a similar analysis for the low-angle strafe concepts. Several aspects of the data in these two tables are noteworthy.

First note that the least experienced individuals (students) consistently show lower correlations both within their own group and with the other groups. Overall the correlations involving students are about .23 compared to an average for the other groups of about .33. Instructor pilots consistently show the most consistency with members of their own group. This is perhaps not surprising since instructors not only know about the execution of the maneuvers, but they also are required to organize what they know so they can communicate it to their students. Overall the correlations suggest that the more experienced individuals agree more among themselves than they agree with the students.

On the other hand, the students do show a reasonable amount of agreement among themselves. Apparently, whatever it is that they think about the concepts being rated, they share the same knowledge to some extent.

Finally, note that the correlations based on the distances derived from the multidimensional scaling are slightly but consistently higher than the correlations based on the original ratings. While this difference is not large, it does suggest that the MDS distances capture at least as much structural information as do the original ratings. As we will see later, the MDS solutions apparently do contain more useful information. One possible explanation for this finding is that the MDS procedure involves the simultaneous consideration of all of the ratings to determine the best relative locations for the concepts. The original ratings, however, only require subjects to consider the concepts two-at-a-time. Apparently, the forced consistency from MDS results in an increase, rather than a loss, of information. The pattern-recognition analysis (which follows) dramatically demonstrates the superiority of the MDS metric over the original ratings.

Table 11

Average Correlations Within Groups and Between Groups

Split-Plane Maneuvers

Rating Scores

	Group				
	IP	GP	UP	IW	Average
IP	.42	.35	.20	.39	.34
GP	.35	.36	.24	.31	.32
UP	.20	.24	.31	.18	.23
IW	.39	.31	.18	.38	.32

Distances in Multidimensional Space

	Group				
	IP	GP	UP	IW	Average
IP	.45	.37	.22	.40	.36
GP	.37	.39	.24	.34	.34
UP	.22	.24	.29	.20	.24
IW	.40	.34	.20	.38	.33

Table 12

Average Correlations Within Groups and Between Groups

Low-Angle Strafe Maneuver

Rating Scores

	Group			
	IP	UP	IW	Average
IP	.44	.20	.39	.34
UP	.20	.32	.24	.25
IW	.39	.24	.36	.33

Distances in Multidimensional Space

	Group			
	IP	UP	IW	Average
IP	.49	.22	.43	.38
UP	.22	.32	.25	.26
IW	.43	.25	.39	.36

PATTERN RECOGNITION ANALYSIS OF CONCEPTUAL STRUCTURES

Conceptual structures provide relational and organizational information about the concepts of a particular domain. In comparing structures across groups of individuals it is possible to define qualitative differences between groups. This type of a comparison is important for delineating how different groups view a particular set of concepts. It is also informative to express differences quantitatively. The purpose of this phase of the project is to define a technique for quantitatively evaluating individual and group differences in conceptual structures of critical flight information.

The objective in this phase of the project is the development of methods for classifying an individual as a member of a particular group based on the individual's conceptual structure. For instance, given someone's conceptual structure for the split-plane maneuvers, is it possible to identify that person as an IP? In addition to classification, the analysis also provides information about the degree to which each individual is associated with each group. The analysis to be described applies the principles and techniques of pattern recognition.

Pattern recognition is an area of artificial intelligence (AI) that is generally concerned with deciding whether an unknown object is a member of a particular class of objects. AI applications often involve computer identification of visual objects, although numerous other uses exist. The only prerequisite for the application of pattern recognition techniques is the necessity to quantify the objects to be recognized. This is accomplished by first identifying a list of features or attributes that best represent the objects and then numerically coding these features. Such a method allows for abstract as well as physical objects to be analyzed. In addition to categorizing objects as members of a particular class, pattern recognition principles also supply information about class and individual differences.

Method

Two types of patterns were formed for each individual tested. One pattern was generated from the conceptual structures derived from a multidimensional scaling (MDS) analysis. Each MDS solution yields a metric formed by taking the distance between each pair of concepts in a multidimensional space. The MDS pattern was created by viewing the attributes of the pattern as values of the metric. This allowed the pattern to preserve the structural properties inherent in the MDS solution. A second pattern was generated by considering the similarity rating given for each pair of concepts as a feature of the pattern. Since this pattern was simply the individual similarity ratings, it lacked the structural properties imposed by scaling techniques. Both methods resulted in patterns with 435 features,

Before the specific analyses are described, a brief overview of the theory of pattern recognition will be presented. Nilsson (1965) provides a general discussion of the principles to be used in the project. Objects to be categorized are represented by a list of feature values in the form of a pattern vector X . The i th element of the vector X represents the value of the i th feature. Since feature values are in the form of real numbers, pattern vectors can be considered as points in a multidimensional space where each dimension represents an attribute of the object. The goal is to develop decision surfaces that will partition the pattern space into regions containing only those points or patterns belonging to a particular class of patterns.

One way of producing decision surfaces is to use linear discriminant functions to decide class membership. This approach assumes that a weighted linear combination of the feature values can determine how a pattern should be classified. A linear discriminant function has the form $g(X) = W_1X_1 + W_2X_2 + \dots + W_dX_d + W_{d+1}$, where $W = W_1, W_2, \dots, W_d$ is a vector of weights. Such a function specifies the equation of a line when $d=2$, the equation of a plane when $d=3$ and the equation of a hyperplane when $d>3$. Classes that can be properly separated with linear discriminant functions are known as linearly separable.

Two methods for generating linear discriminant functions will be used. The first method, known as a minimum-distance classifier, is simple to apply but works only under restricted conditions. With this procedure, a prototype point representing the central tendency of a class of patterns is constructed for each pattern class. Often the prototype point of a class is simply the average of the feature values of all patterns belonging to the class. A minimum-distance classifier computes the distances between each pattern to be categorized and each prototype point and places the pattern into that class associated with the nearest prototype. In the case of two classes, the decision surface separating the patterns is the perpendicular bisector of a line connecting the two prototype points. This approach works well when the patterns of each class cluster tightly around their respective prototype points, and the class clusters are well separated.

A second approach to pattern classification employs a training algorithm that alters a linear discriminant function until it correctly classifies the patterns in a training set. The training procedure alters the function by successive adjustments to the weight vector W which in effect changes the orientation and position of the decision surface. In the case of two linearly separable classes, a weight vector exists that will produce a discriminant function that returns a positive value for all patterns from the first class and a negative value for all patterns from the second class. During the training procedure, if the function returns a correct response for a pattern from the training set, no adjustment is made to the weight vector. If the function returns a negative response for a training pattern from

the first class, the weight vector is corrected by adding a fraction of the pattern vector that was incorrectly classified to the weight vector. This produces a new weight vector $W' = W + cX$, where c is a positive number that controls the extent of the adjustment and is known as the correction increment. If c is large enough, the new weight vector will correctly classify the training pattern. If the discriminant function incorrectly returns a positive value for a training pattern from the second class, a fraction of the pattern is subtracted from the weight vector $W' = W - cX$.

The training procedure consists of presenting the training patterns one at a time and adjusting the weight vector when necessary. The patterns may be presented in any order as long as each pattern is tried. The procedure is terminated as soon as the weight vector correctly classifies all patterns in the training set. Several iterations through the training set may be necessary before a solution is found. The weight vector may be initialized to any convenient set of values including random values.

The first analysis consisted of applying a minimum-distance classifier to all pairs of groups for both the split-plane and low-angle strafe maneuvers. Prototype points for all groups and decision surfaces for separating all pairs of groups were computed. In each application of the minimum-distance classifier, all members of the two groups were used. This provided information about both group and individual differences. The distances from each individual to a decision surface and from each individual to the group prototypes were computed along with the distances between group prototypes.

The second analysis involved computing a decision surface that separated a training set consisting of a limited number of members from two groups and then applying the decision surface to the remaining members of the groups. Decision surfaces were computed with a training algorithm if a minimum-distance classifier did not separate the training sets. Weight vectors were initialized to the weights produced by a minimum-distance classification of the individuals in the limited training set. This minimized the number of iterations needed to produce a solution when the minimum distance classifier failed and also kept the final weight vector as close to the minimum-distance decision surface as possible. The first analysis showed that the classes clustered tightly indicating that when the minimum-distance weights failed to separate the classes, a solution close to these weights was likely. A small correction increment ($c=0.01$) was used to produce minimal change from the minimum-distance weights.

For each pair of groups, a training set of a particular size was randomly chosen, and a decision surface was computed to separate the members of the training set into their respective classes. In the case where a minimum-distance classifier correctly separated the members of the training sets, the resulting discriminant function was then applied to the remaining members of the two groups. If no

solution was found with the minimum-distance classifier, the training algorithm was applied to the subset of selected group members to generate a decision surface which correctly classified all individuals in the training set. The resulting discriminant function was then applied to the individuals who were not included in the training set. This procedure was repeated 100 times for each training set size. The training sets consisted of equal numbers of individuals from each group. The whole procedure was iterated with successively larger training sets until the size of the smaller group was reached.

A final analysis evaluated group differences on a qualitative level. Each of the weights in a discriminant function corresponds to a pair of concepts in the stimulus set. Once a discriminant function that separates two groups is derived, it is possible to identify those concept pairs that contribute the most to discriminating between groups. The most discriminating pairs of concepts correspond to the weights in the weight vector with the greatest absolute values. Large positive weights are associated with pairs of concepts that the first group views as more related than the second group, and large negative weights are associated with pairs of concepts that the second group views as more related than the first group. Weight vectors derived from a minimum-distance classification of the MDS patterns were used for comparing groups.

Results and Discussion

The major finding was that pattern recognition techniques can be used to discriminate classes of flying personnel based on their conceptual structures of critical flight information. Also significant was the result that patterns represented by distances in an MDS solution produced better group separation than patterns based on rating scores.

The first analysis showed that a minimum-distance classifier applied to each pair of groups resulted in well separated groups with only a few erroneous classifications. Table 13 gives the number of members from each group who were classified into each of the groups. Incorrect classifications between two groups indicate that the decision surface generated for those groups does not accurately separate all members. Table 13 shows the classifications for both types of patterns (ratings and MDS) and both sets of stimulus materials (split-plane maneuvers and the low-angle strafe maneuver).

When the minimum-distance classifier was applied to rating data, a small number of misclassifications occurred. For the split-plane maneuvers, all of the misclassifications occurred between IPs and UPTs. The two IPs who were classified as GPs under the ratings were on the GP side of the decision surface separating IPs and GPs. This means that their conceptual structures resembled more closely those of GPs than IPs. Two IPs were also classified as IWSOs, and we will see shortly that these are the same two IPs that were classified as GPs.

Table 13

**Classifications Based on Group Separation
with a Minimum-Distance Classifier**

Split-Plane Maneuvers

	Ratings				Distances in MDS			
	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>UPT</u>	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>UPT</u>
IPs classified as	3	2	2	0	7	0	0	0
GPs classified as	0	9	0	0	0	9	0	0
IWSOs classified as	0	0	4	0	0	0	4	0
UPTs classified as	0	4	1	12	0	0	0	17

Low-Angle Strafe

	Ratings			Distances in MDS		
	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>
IPs classified as	6	0	0	6	0	0
IWSOs classified as	0	6	1	0	7	0
UPTs classified as	0	3	13	0	0	16

These two individuals view the split-plane maneuvers somewhat differently from the other IPs. Table 13 also shows that four of the UPTs have conceptual structures that resemble more closely a GP structure than a UPT structure. An important point is that these misclassifications occur even though the individuals misclassified contributed to defining their group prototype.

The number of misclassifications occurring between two groups reflects both the distance between the groups in the pattern space and also the tightness with which individuals cluster around their respective prototypes. IPs and UPTs appear to be very distinct classes since no IPs were classified as UPTs and no UPTs were classified as IPs for either maneuver. Considering the simplicity of the decision surfaces produced by the minimum-distance approach, the overall results indicate quite distinct classes of individuals.

Table 13 also provides the results of the minimum-distance classifier using the patterns from an MDS solution. Here we find perfect separation of all classes. Apparently the structural information supplied by the MDS procedure maximizes the differences between classes. This finding helps to validate the claim that the MDS technique extracts important structural information from similarity ratings. Additional support for this claim comes from the higher correlations found for individuals within classes using MDS distances in comparison to rating scores (see Tables 11 and 12).

Although the number of misclassifications reflects between-group similarity, a more direct measure is the distance between group prototypes. Shorter distances suggest greater similarity between group conceptual structures. Table 14 shows these distances for all pairs of groups along with a ranking of the distances. Given the superior performance of the MDS patterns, the ranking based on the MDS patterns should be more valid than that of the ratings. Table 14 shows that the most similar classes are IPs and GPs followed closely by IPs and IWSOs. Thus, it is not surprising that the two IPs who were misclassified as GPs were also misclassified as IWSOs. IPs and UPTs are seen to be two of the most dissimilar groups which is also consistent with the finding that no misclassifications occur between these two groups.

Since each individual is represented as a point in the pattern space, it is possible to provide distances that reflect how similar the individual is to each group. Two measures are of particular interest, the distance from an individual to a decision surface and from an individual to the group prototype points. The distance between an individual and the decision surface separating that individual's group from another group reflects the degree to which that individual belongs to the group. Large distances suggest strong identification with the group. The closer the individual is to the decision surface the more similar that person is to the other group. Negative distances indicate that the person is on the wrong side of

Table 14
Distances Between Group Prototypes
for All Pairs of Groups

Split-Plane Maneuvers

	<u>Ratings</u>	<u>Rank</u>	<u>Distances in MDS</u>	<u>Rank</u>
IP-GP	33.36	2	81.30	1
IP-IWSO	38.02	4	82.96	2
IP-UPT	39.14	5	106.29	5
GP-IWSO	30.72	1	92.56	4
GP-UPT	37.90	3	91.31	3
IWSO-UPT	49.41	6	111.96	6

Low-Angle Strafe

	<u>Ratings</u>	<u>Rank</u>	<u>Distances in MDS</u>	<u>Rank</u>
IP-IWSO	25.95	1	76.32	1
IP-UPT	38.97	3	120.83	3
IWSO-UPT	36.10	2	95.87	2

the decision surface and is therefore misclassified. The distance between an individual and a class prototype reveals how strongly that individual represents the average features of that class. The distances from a point in the pattern space to the decision surface and from the point to its prototype do not necessarily correspond because, for example, a point on the edge of the pattern space may be close to the decision surface but far from its prototype.

Tables 15 through 23 give the distances from an individual to both decision surfaces and group prototypes for all individuals. The rating patterns for IPs in Table 15 show that I2 and I7 were the two IPs who were incorrectly classified as GPs and IWSOs. It is interesting to note that I7 is in fact a GP. This individual was placed in the IP class when the only classes available were IPs and IWSOs and then was never reclassified. It is also informative to examine the number of hours of flying time for both I2 and I7 from Table 5 in comparison to the other IPs. Both have considerably more hours than do the other IPs. Their flying time is actually much closer to the GPs' flying time.

An examination of the MDS patterns from Table 15 shows that although all IPs were correctly classified, I2 and I7 have the shortest distances to the decision surface separating IPs and GPs. Generally, there is good correspondence between distances for the ratings and the MDS patterns. When disagreement occurs, it must be attributed to the additional information supplied by MDS. Again, MDS should provide the clearer picture. By rank ordering the distances under the GP column, it is possible to order the IPs in terms of their resemblance to GPs. Similar orderings can be obtained for IPs in comparison to IWSOs and UPTs. The distances from IPs to group prototypes under each class can also be ordered. As seen in Table 15, I3 most closely resembles the prototypical IP on the basis of conceptual structures of the split-plane maneuvers. Similar information can be obtained for the members of the other classes.

The UPTs are particularly interesting since they are currently undergoing training to develop expertise in flying maneuvers. From the individual distances for the UPTs in Tables 18 and 19, it is apparent that some of the UPTs view the split-plane maneuvers more like the experts than do the other UPTs. For instance, U7 was classified both as a GP and a IWSO in addition to being the closest UPT to the IP decision surface. Although no misclassifications occurred with the MDS patterns the same trends occur. This individual appears to be approaching the conceptual structure of the experts more quickly than are the other UPTs.

Table 15

Separation of IPs from Other Groups
Based on a Minimum-Distance Classifier

Split-Plane Maneuvers
I1 through I7 are individual IPs

Rating Scores

	Distances from Decision Surface			IP	Distances from Group Prototypes		
	GP	IWSO	UPT		GP	IWSO	UPT
I1	25.20	34.25	21.86	43.58	59.84	67.11	60.09
I2	-4.13	-6.50	15.43	44.14	40.91	38.13	56.18
I3	18.18	18.45	26.25	41.30	54.03	55.76	61.33
I4	49.29	56.82	14.40	68.90	89.64	95.23	76.65
I5	9.12	9.53	15.99	37.05	44.51	45.80	51.24
I6	32.30	31.17	34.25	51.28	69.19	70.71	72.88
I7	-13.22	-10.64	8.83	45.33	34.25	35.29	52.40
Average from group prototypes:				<u>47.37</u>	56.05	58.29	61.54

Distances in Multidimensional Space

	Distances from Decision Surface			IP	Distances from Group Prototypes		
	GP	IWSO	UPT		GP	IWSO	UPT
I1	34.52	56.93	52.72	105.71	129.57	143.60	149.60
I2	32.22	25.98	39.83	119.56	139.76	136.40	150.87
I3	44.09	42.61	72.90	101.72	132.35	131.97	160.76
I4	52.87	54.32	59.18	108.04	142.37	143.82	155.73
I5	39.83	30.86	42.47	109.18	135.64	130.54	144.74
I6	55.05	43.91	59.03	114.96	148.89	143.18	160.51
I7	25.97	35.76	45.89	111.97	129.46	135.91	149.31
Average from group prototypes:				<u>110.16</u>	136.86	137.92	153.07

Each row of the table represents one IP. Decision surfaces were computed for separating IPs from the three remaining groups. The distance from each IP to a decision surface is shown along with the distance from each IP to each group prototype. Negative distances indicate that the individual is on the wrong side of the decision surface and therefore misclassified.

Table 16

Separation of GPs from Other Groups
Based on a Minimum-Distance Classifier

Split-Plane Maneuvers
G1 through G9 are individual GPs

Rating Scores

	Distances from Decision Surface			Distances from Group Prototypes			
	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>UPT</u>
G1	17.51	7.39	24.20	49.20	35.39	41.30	55.56
G2	7.68	20.24	10.16	44.82	38.69	52.35	47.61
G3	6.53	10.55	13.06	42.36	36.85	44.79	48.45
G4	11.04	26.09	5.41	53.44	46.04	61.01	50.29
G5	6.58	13.31	2.10	38.36	32.13	43.01	34.52
G6	35.58	15.86	35.12	67.96	47.38	56.74	70.05
G7	13.87	16.06	24.43	54.69	45.45	55.25	62.59
G8	30.94	25.96	29.69	65.11	46.64	61.40	66.52
G9	20.40	2.82	26.37	52.49	37.33	39.59	58.24
Average from group prototypes:				52.05	<u>40.66</u>	50.60	54.87

Distances in Multidimensional Space

	Distances from Decision Surface			Distances from Group Prototypes			
	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>UPT</u>
G1	29.85	34.75	44.53	135.06	115.70	140.78	146.69
G2	44.88	46.49	54.97	145.52	117.81	149.95	154.65
G3	24.01	30.21	57.31	128.40	112.71	134.82	151.82
G4	50.97	55.73	29.34	148.58	117.42	155.26	138.36
G5	38.91	34.92	33.20	151.24	128.64	151.70	150.37
G6	58.17	65.18	48.27	157.95	124.45	166.00	155.89
G7	28.65	43.15	44.93	132.55	113.63	144.56	145.31
G8	70.97	88.28	43.82	177.94	141.85	190.96	167.70
G9	19.45	17.83	54.50	131.07	118.39	131.59	154.82
Average from group prototypes:				145.37	<u>121.18</u>	151.74	151.73

Each row of the table represents one GP. Decision surfaces were computed for separating GPs from the three remaining groups. The distance from each GP to a decision surface is shown along with the distance from each GP to each group prototype. Negative distances indicate that the individual is on the wrong side of the decision surface and therefore misclassified.

Table 17

Separation of IWSOs from Other
Groups Based on a Minimum-Distance Classifier

Split-Plane Maneuvers
W1 through W4 are individual IWSOs

Rating Scores

	Distances from Decision Surface			Distances from Group Prototypes			
	<u>IP</u>	<u>GP</u>	<u>UPT</u>	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>UPT</u>
W1	36.26	17.89	37.30	65.72	51.59	39.52	72.45
W2	30.06	17.24	31.51	60.47	49.31	37.03	66.98
W3	5.65	8.84	10.80	42.09	43.43	36.64	49.09
W4	4.08	17.74	19.21	49.73	56.89	46.50	63.73
Average from group prototypes:				54.50	50.31	<u>39.92</u>	63.06

Distances in Multidimensional Space

	Distances from Decision Surface			Distances from Group Prototypes			
	<u>IP</u>	<u>GP</u>	<u>UPT</u>	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>UPT</u>
W1	53.90	47.18	63.20	143.22	142.50	107.56	160.38
W2	74.84	73.47	60.53	167.57	171.07	125.15	170.93
W3	21.36	31.93	43.14	119.50	129.02	103.61	142.81
W4	15.83	32.55	57.05	119.52	132.98	107.97	156.30
Average from group prototypes:				137.45	143.89	<u>111.07</u>	157.61

Each row of the table represents one IWSO. Decision surfaces were computed for separating IWSOs from the three remaining groups. The distance from each IWSO to a decision surface is shown along with the distance from each IWSO to each group prototype. Negative distances indicate that the individual is on the wrong side of the decision surface and therefore misclassified.

Table 18

Separation of UPTs from Other Groups
Based on a Minimum-Distance Classifier

Split-Plane Maneuvers
U1 through U17 are individual UPTs

Rating Scores

	Distances from Decision Surface			Distances from Group Prototypes			
	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>UPT</u>
U1	14.95	-0.45	2.55	66.51	56.73	59.20	57.04
U2	17.07	-3.03	7.52	66.44	53.37	61.81	55.48
U3	11.21	11.70	19.37	45.58	45.68	55.80	34.64
U4	19.47	26.11	31.13	56.04	59.96	68.51	40.20
U5	25.03	35.90	39.89	66.31	71.82	79.87	49.37
U6	21.72	29.88	36.71	75.16	78.82	87.04	62.84
U7	10.37	-4.57	-0.98	58.09	47.08	49.66	50.63
U8	14.76	8.92	15.01	52.97	48.23	55.98	40.63
U9	27.37	36.00	42.89	72.52	76.45	85.76	55.83
U10	16.28	-0.54	4.99	62.92	51.42	56.37	51.82
U11	23.58	37.16	43.73	68.84	75.56	84.94	53.79
U12	21.06	23.97	28.12	56.58	50.05	65.81	39.40
U13	27.13	28.26	32.67	75.48	75.60	82.47	59.78
U14	24.64	35.48	39.20	62.25	68.08	76.28	44.11
U15	15.21	0.86	9.46	69.80	61.21	67.95	60.68
U16	11.41	16.99	23.14	60.07	63.27	70.73	52.10
U17	31.46	39.46	44.62	91.67	94.51	101.74	77.08
Average from group prototypes:				65.13	63.87	71.17	<u>52.08</u>

Each row of the table represents one UPT. Decision surfaces were computed for separating UPTs from the three remaining groups. The distance from each UPT to a decision surface is shown along with the distance from each UPT to each group prototype. Negative distances indicate that the individual is on the wrong side of the decision surface and therefore misclassified.

Table 19

Separation of UPTs from Other Groups
Based on a Minimum-Distance Classifier

Split-Plane Maneuvers

U1 through U17 are individual UPTs

Distances in Multidimensional Space

	Distances from Decision Surface			Distances from Group Prototypes			
	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>IP</u>	<u>GP</u>	<u>IWSO</u>	<u>UPT</u>
U1	61.23	57.37	61.95	181.34	174.20	183.69	140.96
U2	66.10	52.62	75.00	181.13	168.42	188.55	136.96
U3	43.82	35.19	52.22	150.65	151.39	167.88	128.42
U4	62.19	55.60	63.03	189.15	180.86	191.49	150.19
U5	63.05	63.00	57.49	182.09	176.80	180.63	140.55
U6	38.62	26.44	37.63	168.59	158.24	169.23	142.17
U7	36.98	23.21	24.98	165.60	154.27	158.60	139.86
U8	49.62	46.08	61.96	170.14	163.75	179.65	135.64
U9	57.85	56.07	63.02	164.17	157.78	169.60	121.06
U10	67.88	42.93	60.85	177.25	157.56	174.96	130.33
U11	64.67	44.46	61.10	179.92	163.57	179.77	136.51
U12	43.15	47.75	45.83	171.88	170.55	175.02	142.72
U13	57.82	48.31	52.08	172.08	161.68	170.24	131.61
U14	53.54	60.08	69.74	166.32	165.07	178.59	127.59
U15	50.68	38.96	64.92	169.43	158.27	180.20	133.92
U16	34.35	21.57	37.45	165.15	154.59	168.38	141.30
U17	51.97	56.49	62.43	172.49	170.36	180.79	136.77
Average from group prototypes:	172.79	163.96	176.31	136.27			

Each row of the table represents one UPT. Decision surfaces were computed for separating UPTs from the three remaining groups. The distance from each UPT to a decision surface is shown along with the distance from each UPT to each group prototype. Negative distances indicate that the individual is on the wrong side of the decision surface and therefore misclassified.

Table 20

Separation of IPs from Other Groups
Based on a Minimum-Distance Classifier

Low-Angle Strafe
I1 through I6 are individual IPs

Rating Scores

	Distances from Decision Surface		Distances from Group Prototypes		
	<u>IWSO</u>	<u>UPT</u>	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>
I1	26.30	20.51	43.13	56.92	58.81
I2	3.24	14.30	32.23	34.75	46.41
I3	20.65	10.73	54.67	63.72	61.84
I4	8.41	17.43	28.48	35.32	46.58
I5	1.32	21.32	41.67	42.49	58.30
I6	17.62	32.61	56.23	63.85	72.52
Average from group prototypes:			<u>42.74</u>	49.51	57.41

Distances in Multidimensional Space

	Distances from Decision Surface		Distances from Group Prototypes		
	<u>IWSO</u>	<u>UPT</u>	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>
I1	54.02	70.32	103.18	137.45	166.25
I2	36.05	62.14	106.81	130.04	162.56
I3	15.82	33.90	119.01	128.75	149.51
I4	35.29	70.55	97.38	121.94	162.89
I5	57.26	69.51	134.06	163.44	186.46
I6	30.45	56.07	119.50	137.63	166.82
Average from group prototypes:			<u>113.32</u>	136.54	165.75

Each row of the table represents one IP. Decision surfaces were computed for separating IPs from the three remaining groups. The distance from each IP to a decision surface is shown along with the distance from each IP to each group prototype. Negative distances indicate that the individual is on the wrong side of the decision surface and therefore misclassified.

Table 21

Separation of IWSOs from Other Groups
Based on a Minimum-Distance Classifier

Low-Angle Strafe
W1 through W7 are individual IWSOs

Rating Scores

	Distances from Decision Surface		Distances from Group Prototypes		
	<u>IP</u>	<u>UPT</u>	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>
W1	22.16	36.12	60.20	49.74	71.28
W2	15.65	14.42	45.41	35.36	47.86
W3	9.81	25.51	42.04	35.47	55.68
W4	12.39	17.99	54.68	48.45	60.38
W5	7.51	-17.61	75.48	72.85	63.53
W6	7.49	15.64	39.53	34.26	47.99
W7	15.81	34.25	53.30	44.95	67.03
Average from group prototypes:			52.95	<u>45.87</u>	59.11

Distances in Multidimensional Space

	Distances from Decision Surface		Distances from Group Prototypes		
	<u>IP</u>	<u>UPT</u>	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>
W1	27.63	58.49	129.55	112.10	155.23
W2	56.30	44.06	145.20	111.75	145.51
W3	31.49	68.82	129.03	108.83	159.41
W4	31.98	40.32	139.63	120.89	150.21
W5	69.28	31.11	193.33	163.71	181.48
W6	19.65	43.06	124.96	112.32	145.27
W7	30.80	59.11	132.40	113.27	156.47
Average from group prototypes:			142.01	<u>120.41</u>	156.23

Each row of the table represents one IWSO. Decision surfaces were computed for separating IWSOs from the three remaining groups. The distance from each IWSO to a decision surface is shown along with the distance from each IWSO to each group prototype. Negative distances indicate that the individual is on the wrong side of the decision surface and therefore misclassified.

Table 22

Separation of UPTs from Other Groups
Based on a Minimum-Distance Classifier

Low-Angle Strafe
U1 through U16 are individual UPTs

Rating Scores

	Distances from Decision Surface		Distances from Group Prototypes		
	<u>IP</u>	<u>IWSO</u>	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>
U1	7.36	-1.72	51.93	44.71	46.08
U2	11.60	4.56	49.68	43.51	39.55
U3	29.15	35.96	65.94	68.36	45.57
U4	27.22	27.41	67.99	66.93	50.01
U5	16.95	4.60	82.66	76.44	74.24
U6	7.05	-4.04	54.49	46.13	49.19
U7	12.70	2.31	58.80	51.32	49.67
U8	31.54	40.76	77.06	80.14	58.99
U9	7.28	-2.56	54.49	47.09	49.01
U10	28.63	44.02	78.89	84.68	63.19
U11	20.44	22.39	55.11	55.33	38.00
U12	11.19	7.93	67.47	65.21	60.66
U13	18.53	19.68	57.72	57.51	43.44
U14	15.22	8.03	69.84	65.35	60.75
U15	27.89	39.58	73.30	77.83	56.57
U16	39.01	39.88	91.78	90.89	73.37
Average from group prototypes:			66.07	63.84	<u>53.64</u>

Each row of the table represents one UPT. Decision surfaces were computed for separating UPTs from the three remaining groups. The distance from each UPT to a decision surface is shown along with the distance from each UPT to each group prototype. Negative distances indicate that the individual is on the wrong side of the decision surface and therefore misclassified.

Table 23

Separation of UPTs from Other Groups
Based on a Minimum-Distance Classifier

Low-Angle Strafe

U1 through U16 are individual UPTs

Distances in Multidimensional Space

	Distances from Decision Surface		Distances from Group Prototypes		
	<u>IP</u>	<u>IWSO</u>	<u>IP</u>	<u>IWSO</u>	<u>UPT</u>
U1	44.98	32.21	179.23	166.14	145.78
U2	61.68	49.43	184.30	169.72	138.07
U3	79.67	66.81	190.52	173.83	130.57
U4	62.93	56.42	194.63	183.83	150.57
U5	58.39	37.43	184.78	165.56	141.54
U6	69.89	62.82	188.00	175.60	135.84
U7	66.20	59.78	193.22	181.99	146.07
U8	68.56	53.61	173.44	155.19	116.25
U9	63.69	52.99	180.27	165.98	130.78
U10	58.86	49.00	168.78	154.67	119.43
U11	67.67	55.88	201.38	187.66	155.57
U12	19.66	15.18	165.18	159.77	150.11
U13	65.83	62.59	184.99	175.07	135.33
U14	49.09	41.74	169.20	158.09	129.48
U15	55.38	37.84	183.86	166.98	142.91
U16	74.16	54.82	180.42	159.49	120.90
Average from group prototypes:			182.64	168.72	<u>136.83</u>

Each row of the table represents one UPT. Decision surfaces were computed for separating UPTs from the three remaining groups. The distance from each UPT to a decision surface is shown along with the distance from each UPT to each group prototype. Negative distances indicate that the individual is on the wrong side of the decision surface and therefore misclassified.

As mentioned previously, class separation depends on both the distance between group prototypes and the closeness with which members cluster around their group prototype. Tables 15 through 23 give a measure of class clustering in the form of the average distance from the class prototype to each class member. Shorter distances suggest more homogeneous classes with greater consistency in the individual conceptual structures. The average distance from the individual to their own group prototype is the value underlined in the tables. For both maneuvers, the IPs cluster most tightly while UPTs are the most variable. This is reasonable considering that IPs follow standard procedures for presenting the maneuvers and have probably developed similar ways of thinking about them. UPTs on the other hand are still learning the material and have different views about how these concepts are related.

All of the classification results reported so far have come from applying discriminant functions to members of classes from which the discriminant functions were originally derived. Although this provides useful information about class and individual differences, it is not a direct test of the ability of discriminant functions to categorize new members of known classes. The second analysis involved generating a discriminant function on the basis of a limited training set from two classes and then using the function to place new and unknown members into one of the two classes.

The results of the classifications are given in Tables 24 and 25 for the split-plane maneuvers and Table 26 for the low-angle strafe maneuver. The tables give the total number of individuals for which a classification was attempted, followed by the percentage of those correctly classified and the probability of randomly classifying at least this number. Since 100 different randomly chosen training sets were used for each training set size, the number of classifications attempted is always 100 times the number of remaining members in the two classes.

The classification of unknown members was quite successful. Table 24 shows that with only one member each from the IPs and GPs on which to base a decision surface, 798 out of 1400 remaining IPs and GPs were classified correctly. Performance was even better for MDS patterns where 949 of the 1400 individuals were correctly classified. These results are more impressive if we consider that two of the seven IPs resemble GPs. In general, classification improves as the distance between classes in the pattern space increases. With only two members each from the IPs and UPTs, it is possible to classify correctly the remaining 20 members 95 percent of the time. Table 26 shows that the classification was poorest for IPs and IWSOs with the low angle strafe maneuver. In Table 14 the distances between group prototypes show that IPs and IWSOs are the closest pair of groups for both ratings and distances in MDS.

Classification generally improves also as the size of the training set increases. This is expected since the discriminant function is derived from a larger more representative sample. Exceptions sometimes occur when a few members in one class strongly resemble members of the other class. In this case, when the training set size is small, the chances of using one of the deviant class members to derive the discriminant function is also small. This results in generally good performance over the 100 trials. But as the training set size increases, the chances of basing the discriminant function on one of the deviant members increases. The result is increased difficulty in classifying the remaining members. Related to this is a factor that influences the probability measure. As the number of classifications attempted declines, higher percentages of correct classification are needed to maintain previous probability levels.

Discriminant functions based upon the MDS patterns resulted in better classification of unknown members compared to the rating patterns. The average percentage of correct classifications for the MDS patterns was significantly greater than the average for the ratings, $t(106)=5.95$, $p<.001$. As mentioned previously, this superior performance can be attributed to the additional structural information supplied by MDS.

It is important to note that the pattern recognition analysis has been performed on a limited number of individuals. Groups have ranged from 4 to 17 members. Traditional applications of pattern recognition often use large numbers of patterns to insure that decision surfaces reflect general class distinctions. The success seen in the current analysis with a limited number of patterns suggests considerable potential for future applications. Decision surfaces based on large representative groups may prove to be even more effective in classifying pilots on the basis of conceptual structures.

Table 24

Classification of Groups Members
on the Basis of Limited Training Sets

Split-Plane Maneuvers

Training		#Classified	Ratings		Distances in MDS	
Set	Size		%Correct	Prob*	%Correct	Prob*
IPs	QPs					
1	1	1400	57	.001	68	.001
2	2	1200	67	.001	77	.001
3	3	1000	67	.001	82	.001
4	4	800	68	.001	84	.001
5	5	600	62	.001	87	.001
6	6	400	52	ns	87	.001
7	7	200	51	ns	84	.001
Total		5600	63	.001	79	.001

Training		#Classified	Ratings		Distances in MDS	
Set	Size		%Correct	Prob*	%Correct	Prob*
IPs	IWSOs					
1	1	900	53	.05	56	.001
2	2	700	57	.001	60	.001
3	3	500	61	.001	63	.001
4	4	300	71	.001	67	.001
Total		2400	58	.001	60	.001

Training		#Classified	Ratings		Distances in MDS	
Set	Size		%Correct	Prob*	%Correct	Prob*
IPs	UPTs					
1	1	2200	65	.001	79	.001
2	2	2000	77	.001	95	.001
3	3	1800	78	.001	98	.001
4	4	1600	83	.001	100	.001
5	5	1400	89	.001	100	.001
6	6	1200	91	.001	100	.001
7	7	1000	96	.001	100	.001
Total		11200	80	.001	94	.001

* Probability of randomly classifying at least the number of individuals correctly classified (ns=not significant).

Table 25

Classification of Groups Members
on the Basis of Limited Training Sets

Split-Plane Maneuvers

Training		#Classified	Ratings		Distances in MDS	
Set	Size		%Correct	Prob*	%Correct	Prob*
OPs	IWSOs					
1	1	1100	58	.001	62	.001
2	2	900	64	.001	71	.001
3	3	700	65	.001	76	.001
4	4	500	70	.001	76	.001
Total		3200	63	.001	70	.001

Training		#Classified	Ratings		Distances in MDS	
Set	Size		%Correct	Prob*	%Correct	Prob*
OPs	UPTs					
1	1	2400	62	.001	79	.001
2	2	2200	70	.001	89	.001
3	3	2000	74	.001	93	.001
4	4	1800	76	.001	95	.001
5	5	1600	76	.001	95	.001
6	6	1400	76	.001	95	.001
7	7	1200	73	.001	95	.001
8	8	1000	73	.001	96	.001
9	9	800	72	.001	98	.001
Total		14400	72	.001	92	.001

Training		#Classified	Ratings		Distances in MDS	
Set	Size		%Correct	Prob*	%Correct	Prob*
IWSOs	UPTs					
1	1	1900	68	.001	76	.001
2	2	1700	81	.001	93	.001
3	3	1500	81	.001	94	.001
4	4	1300	78	.001	95	.001
Total		6400	76	.001	89	.001

* Probability of randomly classifying at least the number of individuals correctly classified (ns=not significant).

Table 26

Classification of Groups Members
on the Basis of Limited Training Sets

Low-Angle Strafe

Training		#Classified	Ratings		Distances in MDS	
Set	Size		%Correct	Prob*	%Correct	Prob*
IPS	IWSOs					
1	1	1100	49	ns	56	.001
2	2	900	43	ns	54	.01
3	3	700	45	ns	53	ns
4	4	500	47	ns	55	.05
5	5	300	43	ns	53	ns
6	6	100	56	ns	56	ns
Total		3600	46	ns	55	.001

Training		#Classified	Ratings		Distances in MDS	
Set	Size		%Correct	Prob*	%Correct	Prob*
IPS	UPTs					
1	1	2000	59	.001	84	.001
2	2	1800	72	.001	96	.001
3	3	1600	73	.001	96	.001
4	4	1400	81	.001	97	.001
5	5	1200	79	.001	97	.001
6	6	1000	80	.001	95	.001
Total		9000	73	.001	94	.001

Training		#Classified	Ratings		Distances in MDS	
Set	Size		%Correct	Prob*	%Correct	Prob*
IWSOs	UPTs					
1	1	2100	58	.001	69	.001
2	2	1900	62	.001	88	.001
3	3	1700	65	.001	91	.001
4	4	1500	67	.001	92	.001
5	5	1300	67	.001	93	.001
6	6	1100	60	.001	93	.001
7	7	900	54	.001	87	.001
Total		10500	62	.001	87	.001

* Probability of randomly classifying at least the number of individuals correctly classified (ns=not significant).

The final analysis on the qualitative differences between groups examined the distance between each pair of concepts in a group's conceptual structure. The result was a list of the concept pairs that were most different in the conceptual structures for two groups. The list is separated into concept pairs that one group views as more related than the other group. Later in this report, a detailed analysis of IP and UPT conceptual structures is given based on a general weighted network. To allow a comparison of the upcoming analysis with the results of the pattern recognition techniques, Table 27 shows those split-plane concepts that lead to the most disagreement between IPs and UPTs.

The major goal of this phase of the project has been to demonstrate both the feasibility and utility of applying the techniques and principles of pattern recognition to conceptual structures of critical flight information. The general finding is that pattern recognition techniques appear to be sensitive enough to detect subtle differences between both groups and individuals. In addition, these differences often seem to have "real-world" significance. Many of the findings may have relevance to selection and training. As discussed later in this report, a beginning pilot's knowledge of split-plane maneuvers begins as a fairly disorganized set of relations. As the person undergoes training and gains experience in these maneuvers the conceptual structures should begin to evolve into structures that more closely resemble those of experienced pilots. The results of this part of the project suggest the possibility of tapping into this developmental process and classifying a person at a particular stage of conceptual development.

Table 27

The Most Discriminable Pairs of Concepts
for Distinguishing IPs from UPTs

Split-Plane Maneuvers

IPs View These Pairs as More Related Than UPTs

LOW YO YO - CUTOFF	HIGH YO YO - QUARTER PLANE
HIGH YO YO - BARREL ROLL	HIGH YO YO - RADIAL G
QUARTER PLANE - RELATIVE ENERGY	BARREL ROLL - ASPECT ANGLE
QUARTER PLANE - VERTICAL MANEUVERING	GUNS - CUTOFF
GUNS - LEAD PURSUIT	ANGLE OFF - 6 O'CLOCK
CUTOFF - SNAPSHOT	6 O'CLOCK - HEAT
POWER SETTING - EXTENSION	ACCELERATION - EXTENSION
SWITCHOLOGY - WEAPONS PARAMETERS	RADIAL G - LIFT VECTOR
RADIAL G - VERTICAL MANEUVERING	SMASH - EXTENSION
HEAT - WEAPONS PARAMETERS	SNAPSHOT - LEAD PURSUIT

UPTs View These Pairs as More Related Than IPs

LOW YO YO - HIGH YO YO	OVERTAKE - PURE PURSUIT
AIRSPPEED - PURE PURSUIT	ANGLE OFF - CUTOFF
ANGLE OFF - 3-9 LINE	CUTOFF - 6 O'CLOCK
CUTOFF - CORNER VELOCITY	CUTOFF - LAG PURSUIT
6 O'CLOCK - SNAPSHOT	6 O'CLOCK - LEAD PURSUIT
POWER SETTING - LEAD PURSUIT	ACCELERATION - LIFT VECTOR
SMASH - HEAT	SMASH - PURE PURSUIT
HEAT - LEAD PURSUIT	SNAPSHOT - LAG PURSUIT
3-9 LINE - EXTENSION	LAG PURSUIT - LEAD PURSUIT
CORNER VELOCITY - LEAD PURSUIT	PURE PURSUIT - LEAD PURSUIT

GENERAL WEIGHTED NETWORKS

An understanding of the underlying conceptual structure of critical flight information can be advanced by determining the global relationships among the concepts as we have done using conventional scaling techniques (e.g., MDS). However, representing local structure (i.e., detailed relationships) among critical flight concepts is quintessential to a full appreciation of fighter pilots' conceptual data bases. Theoretically, a general weighted network can accomplish this goal.

A general weighted network is a configuration in which concepts are depicted by nodes and relationships are depicted by links connecting the nodes. The links are assigned a value or weight that reflects the strength of the relationship between the nodes. The value reflects the distance from one node to another along that link; the shorter the link, the closer the nodes. The network is general in that constraints are not placed on the possible relations that can be represented. For example, the hierarchical constraint found in cluster analysis is not placed on general weighted networks. With this constraint removed, the representation becomes more sensitive to local relations other than hierarchical ones but hierarchical relations may still be present (Christofides, 1975; Fillembaum & Rapaport, 1971).

Networks have formed the basis of research in a number of areas of cognitive science. Several psychological and artificial intelligence models of conceptual structure are based on such networks. Work in graph theory is centrally concerned with properties of general networks. While important theoretical and formal work has been conducted on these structures, no methods have been available to produce networks from empirically obtained measures of psychological distance. We developed a network algorithm which produces general weighted networks (GWN) to apply to the rating data. Recently we discovered another algorithm developed by Hutchinson (1981). Here we will discuss our algorithm, GWN, and its application.

The central problem in constructing a network from psychological distance data is to determine which links to place in the network. For N concepts, the possible number of links lies between $N-1$ links for a minimally connected network (MCN) and $(N \times (N-1))/2$ links for all possible connections.

GWN decides whether to add a link to the existing network for any two concepts, say, GUNS and CUTOFF, in the following way. The empirical distance between the two concepts is compared with the shortest chain (sequence of links) already existing in the network connecting GUNS and CUTOFF. Such a chain might be GUNS-LEAD PURSUIT-CUTOFF, or more generally, GUNS- X_1 - X_2 - . . . - X_n -CUTOFF, where the X s represent intervening nodes of the chain. GWN assumes that for a person to decide on the relatedness of GUNS and CUTOFF search is directed along

the network from each concept. The searches will intersect, at some concept X_i , along the shortest chain connecting the two concepts. The distance before this intersection occurs is taken by GWN as the shortest distance between the concepts. If the empirical distance is longer than the shortest distance currently in the network, then GWN does not add a link since the new link would be redundant with the shortest chain. If the empirical distance is shorter than the evaluated distance of the shortest current chain, then GWN adds a link connecting GUNS and CUTOFF because the psychological distance is smaller than would be allowed by the existing network. By iterating this procedure starting with the smallest empirical distance and proceeding with all distances in order of their magnitude, GWN adds links to the network and can create networks of varying complexity.

MCN: The Skeletal Structure. For any set of N concepts, those concepts can be formed into a network (more specifically a tree) with $N-1$ links. In such a network or tree, each concept is reachable from every other concept. Each node, not yet connected to the network, is connected by finding the shortest link between it and an element of the network. This solution minimizes the average distance from all concepts X_i to all concepts X_j for $N-1$ links. The MCN has a special status in that the MCN links will appear, by definition, in all connected networks regardless of how elaborate. In a sense, the MCN represents the backbone of the network and may have a special status in the conceptual representation. The MCN produced by GWN turns out to be the shortest spanning subtree proposed by Kruskal (1956).

MEN: The Integral Connections. The MEN is the minimal network that includes more links than the simple tree structure of the MCN. The MEN allows additional interconnections among concepts that produce the most efficient connections with a minimal number of links. Unlike the MCN, the MEN does not have a logical bound on the number of links that can be found in the network. Also unlike the MCN, cycles can be introduced into the representation. Cycles are of particular interest in that they are chains that begin and terminate on the same node.

We analyzed the psychological distance data from UPTs, IPs, GPs, and IWSOs for split-plane maneuvers and the low-angle strafe maneuver using GWN. The resulting networks for IPs and UPTs appear in Figures 10 to 16. The nodes in the networks are located on the page according to the two-dimensional multidimensional scaling solutions for the IPs. One of the problems of representing the networks is arranging the nodes. Using the MDS solution solves that problem and has the advantage of depicting both dimensional information and network information in the same representation. The MDS solution for the IPs is used for all networks to facilitate comparisons between IP and UPT networks. In the figures, the MCNs are represented by solid lines and the dotted lines represent the additional links added in the MEN solutions.

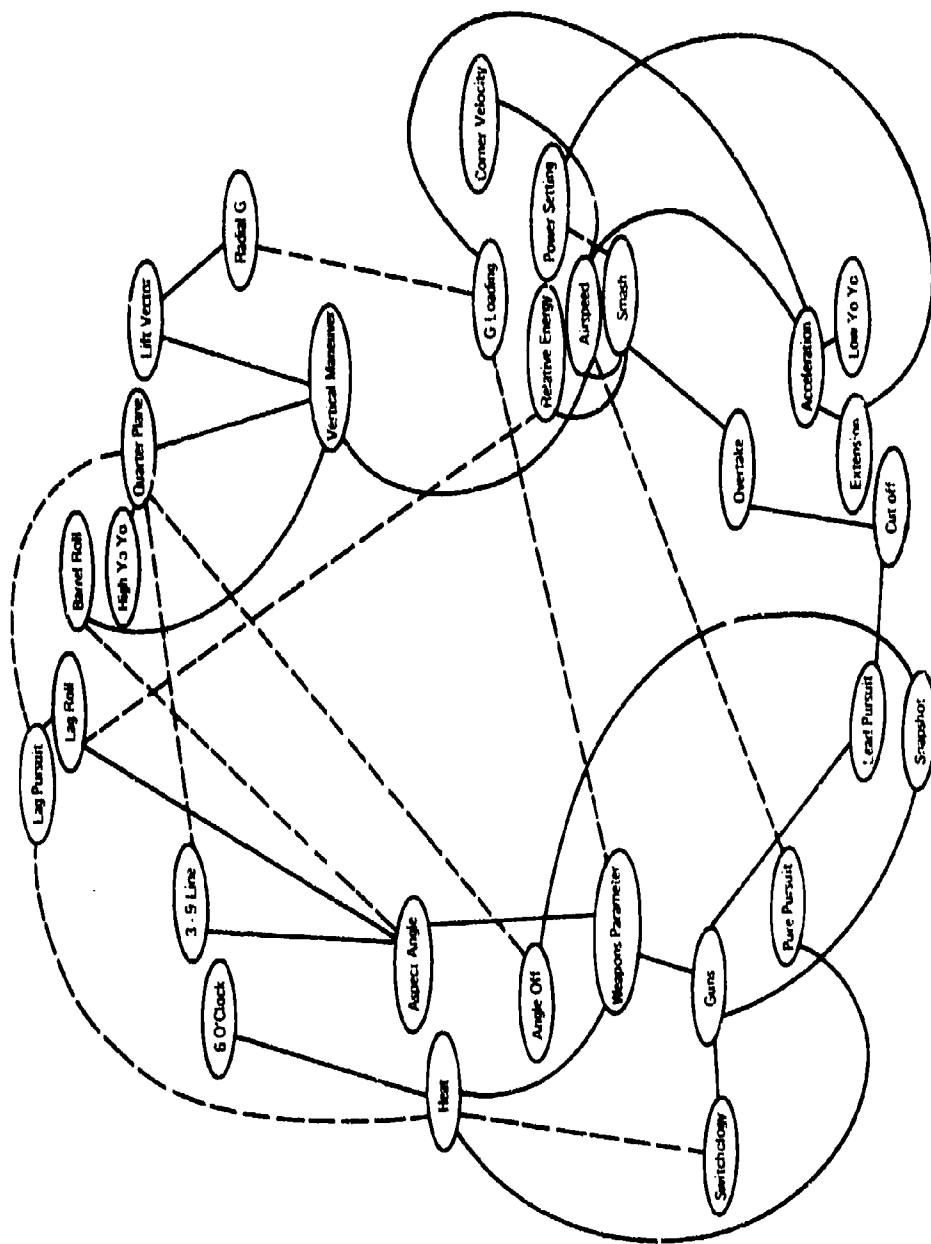


Figure 11. Minimal Elaborated Network by GWN of Split Plane concepts for Instructor Pilot. Solid lines are MCN links. Dotted lines are links added in the MEN.

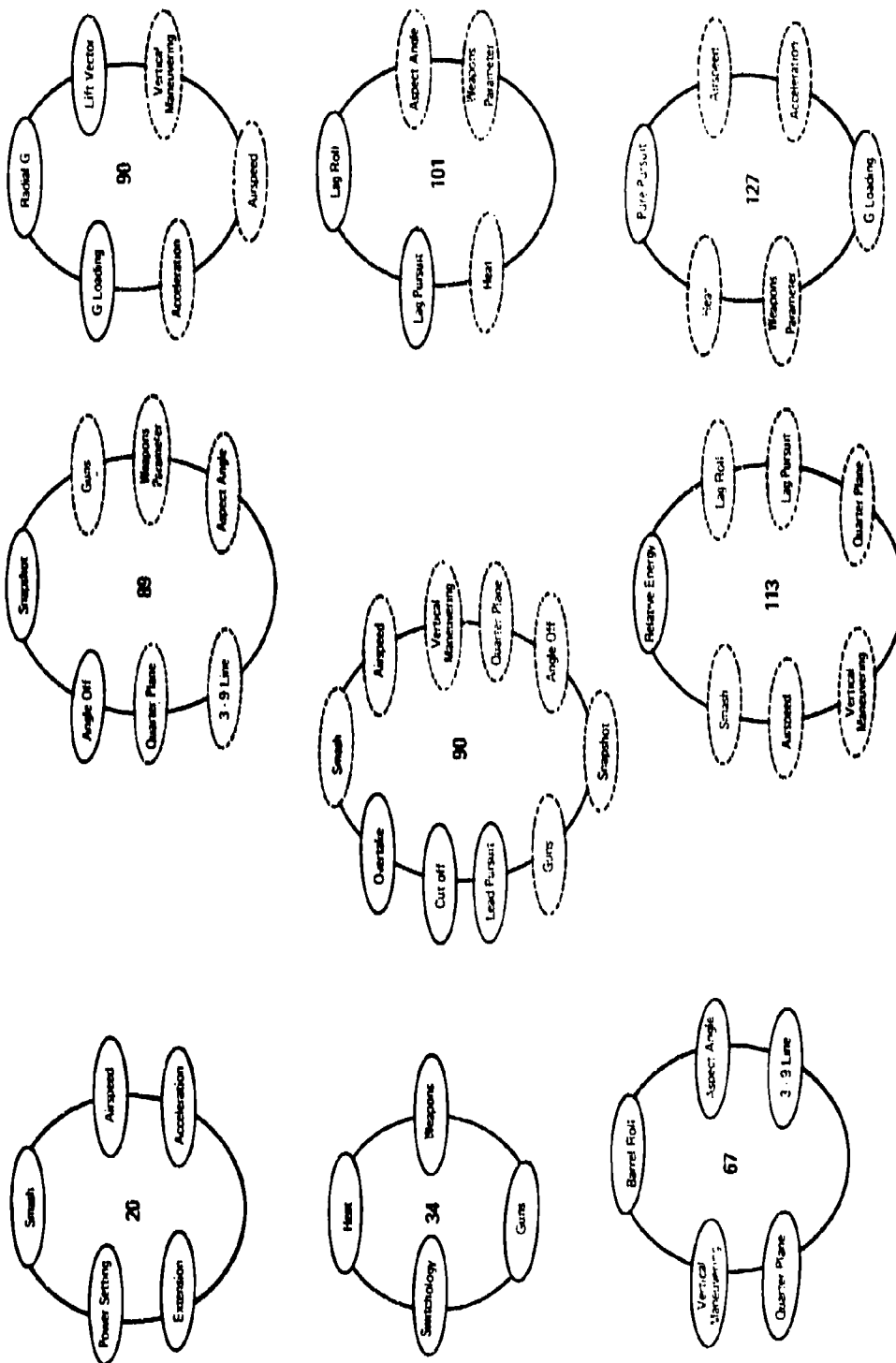


Figure 12. Minimum Cycles for each Split Plane concept for Instructor Pilots. Solid nodes use that cycle as a minimum.

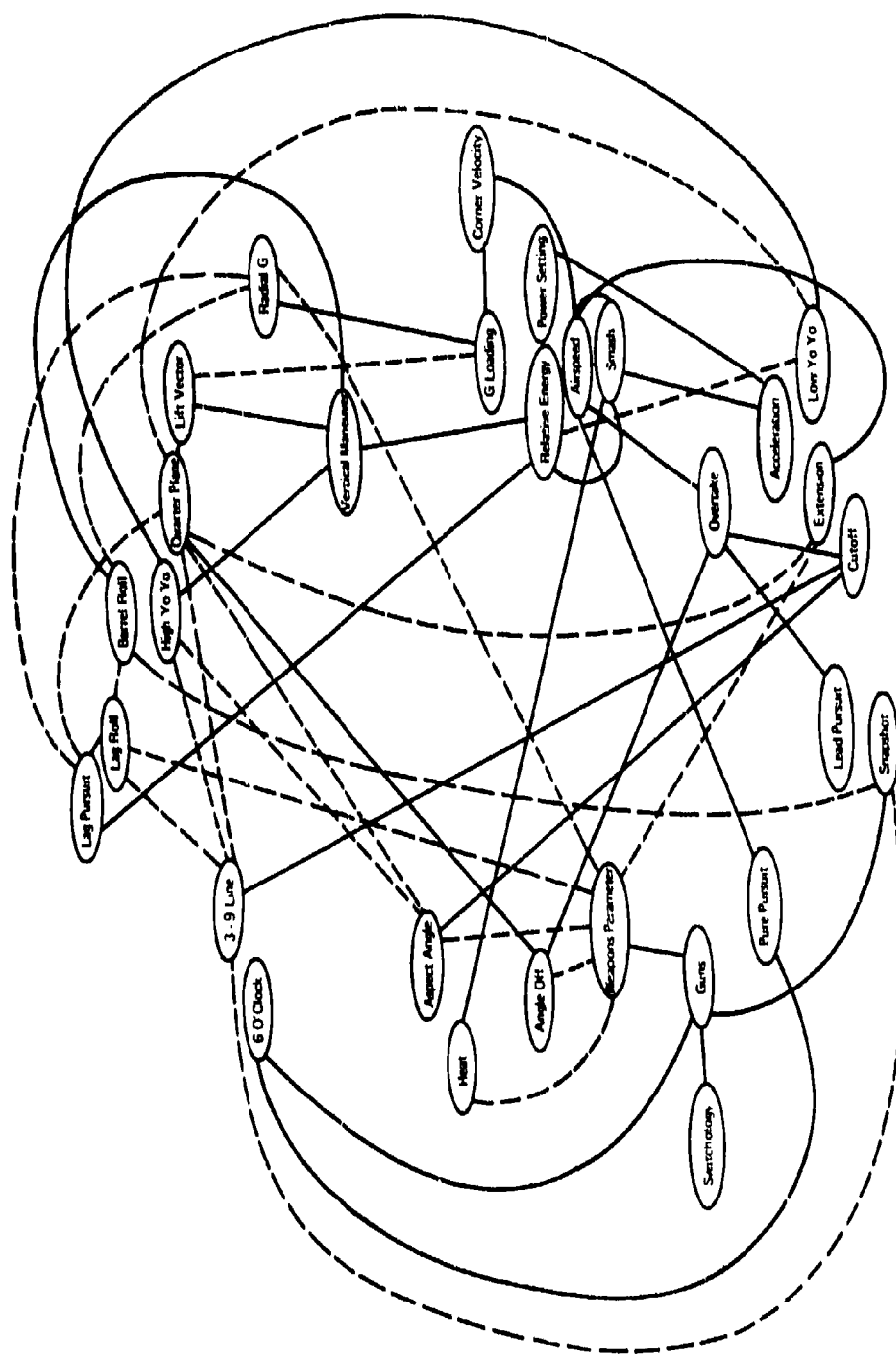


Figure 13. Minimal Elaborated Network by GWN of Split Plane concepts for Undergraduate Pilot Trainees. Solid lines are MCN links.

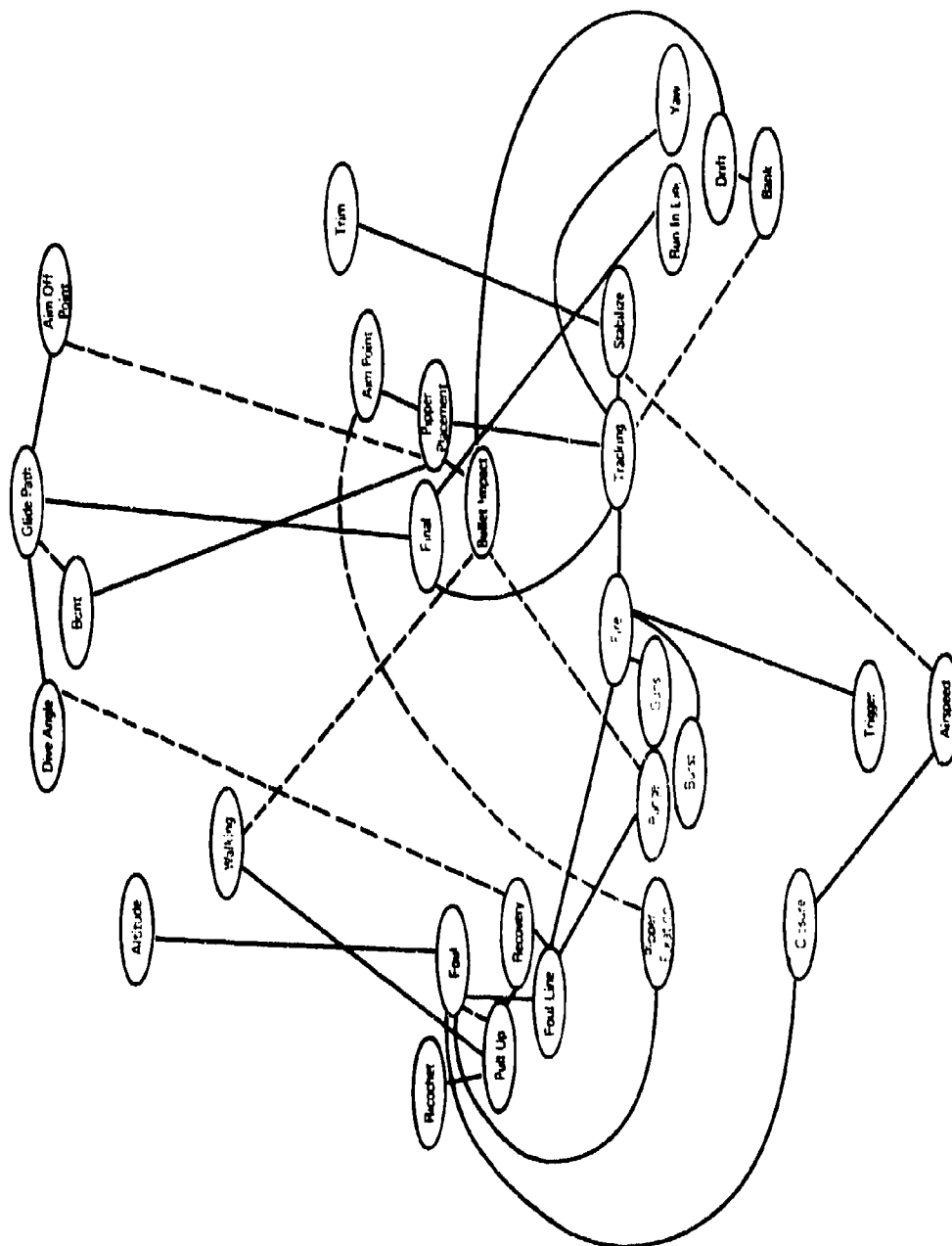


Figure 14. Minimal Elaborated Network by GWN of Sraife concepts for Instructor Pilots. Solid lines are MCN links.

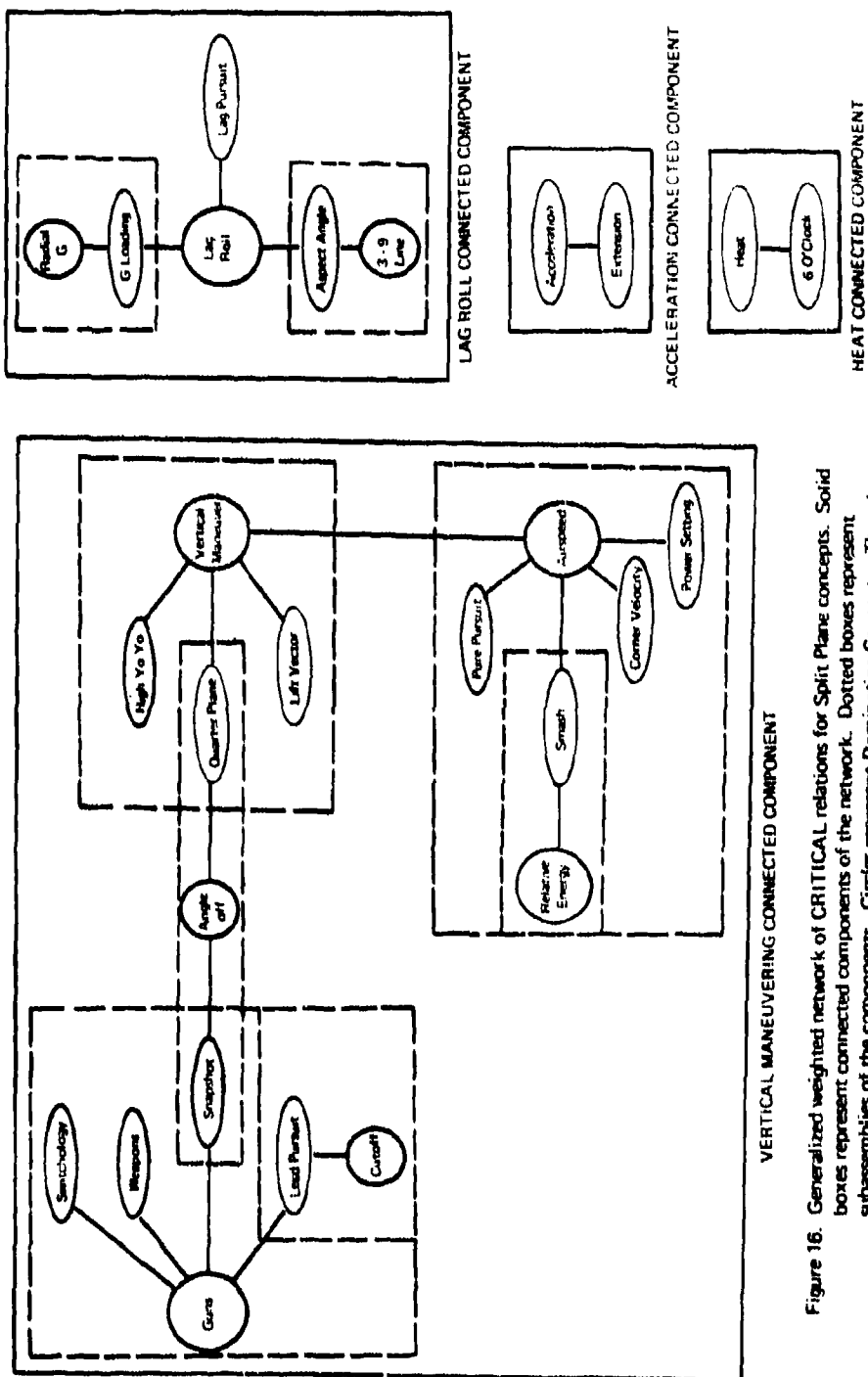


Figure 16. Generalized weighted network of CRITICAL relations for Split Plane concepts. Solid boxes represent connected components of the network. Dotted boxes represent subassemblies of the components. Circles represent Dominating Concepts. Though not shown, Vertical Maneuvering also belongs in the Airspeed Subassembly and vice versa.

The network derived from the student data is considerably more complex than the IP network. The elaborated student network has 51 links compared to 40 for the instructor network. Apparently, the instructors have a better organized structure for these concepts; at least it is more elegant. Surprisingly, the GP network was even more complex than the UPT network. Perhaps the necessity of communicating the concepts to students contributes to the simplicity of the instructors' organization.

We will analyze, in depth, the network of split-plane concepts for the IPs and then will make comparisons across networks. The IP network was chosen for several reasons: a) The network contains several theoretical highlights of networks, b) The network is the representation of an expert and is therefore of practical importance, c) it is similar to the other group of professional pilots (i.e. GPs), d) the IPs have direct communication with the UPTs, and e) the IPs produced the most elegant structure, which will simplify discussion considerably.

Split Plane Network for Instructor Pilots. We analyzed the empirical distance data for the 30 SPLIT PLANE concepts using GWN. GWN produced the MCN shown in Figure 10 for the instructor pilots. The network is composed of 29 links with an average link length of 10.4 and a standard deviation of 7. The shortest link is between GUNS and SNAPSHOT (1 unit) and the longest links are LAG ROLL-ASPECT ANGLE and HEAT-PURE PURSUIT (26 units). A great deal of structure is apparent even in the skeletal configuration of the MCN. The MCN for these data is far from the simple structures in which one concept links to the remaining 29 concepts or in which each concept links to two other concepts forming a straight-line chain. Rather there are several concepts that link to multiple concepts (GUNS, HEAT, ASPECT ANGLE, VERTICAL MANEUVERING, ACCELERATION, SMASH, AIRSPEED).

When GWN elaborates the MCN to form the MEN, 11 additional links are added, making a total of 40 links, with an average link length of 14.5, standard deviation of 10.5, and maximum link length of 44 units (AIRSPEED-PURE PURSUIT). Figure 11 shows the MEN solution with the MCN links as solid lines and the additional 11 links as dotted lines. The additional links seem to integrate the overall network by connecting concepts closely allied with flight to concepts closely allied with weapons. Some of these connections are indirect (e.g., QUARTER PLANE to LAG PURSUIT) while others are quite direct (e.g., G LOADING to WEAPONS PARAMETERS). The three new links from QUARTER PLANE certainly help interconnect the overall network and, in addition, make QUARTER PLANE a central concept in the network. Note also that only four concepts are terminal (i.e., connect to only one other concept): HI YO YO, LO YO YO, 6 O'CLOCK, and CORNER VELOCITY.

Another very important form of integration produced by the additional links of the MEN is the establishment of cycles. Cycles are chains of links through the network that allow a return to the starting point without backtracking (i.e., without returning over the same link). Recall that with the MCN configuration of 29 links, cycles were not possible. The addition of the 11 links in the MEN produced nine minimum distance cycles. Cycles can be found for each nonterminal node in the network. The terminal nodes obviously cannot be in cycles since there is only one entry point to the concept.

Viewing the nine cycles in Figure 12 gives a better picture of the structure present in the MEN. In principle there could be 26 minimum cycles in the MEN, one for each non-terminal concept. However, only nine unique minimum cycles are present in the MEN indicating that several concepts share the same cycle. The shortest cycle is only 20 units long and is used by five concepts as the minimum cycle. The longest cycle is 127 units long and is the minimum cycle for only one concept (i.e., PURE PURSUIT).

Members of the same cycle may have a psychological relationship among themselves that is not found between concepts from different cycles. For example, the three shortest cycles are of particular interest, not only because they are the most compact, but also because each member of the cycle uses that cycle as the shortest route through the network and back. These cycles appear to form meaningful organizational units:

(AIRSPEED-SMASH-POWER SETTING-EXTENSION-ACCELERATION)

(GUNS-SWITCHOLOGY-HEAT-WEAPONS PARAMETERS)

(QUARTER PLANE-VERTICAL MANEUVERING-
BARREL ROLL-ASPECT ANGLE-3/9 LINE)

Another means of identifying substructures within the MEN is the formation of conceptual assemblies. Conceptual assemblies are formed by finding the smallest number of concepts that dominate all the other concepts in the network. In other words, from this set of dominating concepts (DCs) all other concepts can be reached by traversing one link. Such a set is referred to in graph theory as externally stable. The problem of finding such a set is analogous to determining the number and locations of, say, army posts to guard cities (nodes) connected by major highways (links) or hospitals to service neighborhoods connected by streets. Often several such sets satisfy the requirements of an externally stable set. In forming assemblies, we placed the additional restriction that the set be as close as possible to internally stable. An internally stable set is a set of concepts with no shared links. Thus, we attempted to find the set of DCs that had a link with every other concept in the network but with no links to other DCs.

The DCs for this network were GUNS, HEAT, QUARTER PLANE, ACCELERATION, SMASH, CORNER VELOCITY, RADIAL G, CUTOFF, and ASPECT ANGLE. Assemblies are composed of the DC and all concepts that it dominates. For example, the GUNS assembly contains GUNS, SWITCHOLOGY, WEAPONS PARAMETERS, SNAPSHOT, and LEAD PURSUIT. Just as cycles partition the MEN into a small number of comprehensible subnetworks (i.e., nine) so do assemblies break down the large amount of data represented in the network into a smaller number of meaningful units, in this case nine.

The network of split-plane concepts for the instructor pilots highlights a number of local relationships that are not apparent in the more traditional scaling techniques that we have used. The networks themselves, MCN and MEN, reduce a huge amount of data in the form of an $N \times N$ distance matrix to a much smaller set of data. These networks can be reduced still further by isolating minimum cycles or DC assemblies. An understanding of the local relationships among concepts or among cycles or assemblies makes it possible to compare experienced pilots with those training to become pilots. With other techniques, say MDS, only gross global comparisons can be made between the groups. With the network representation, and with the pattern classifier discussed elsewhere in this report, individual concepts can be examined and the extent to which the organization is the same for experienced and novice pilots can be determined. Further, novice pilots may differ from experienced pilots either because the novices are missing critical links for a particular concept (underdefined concepts) or because they have additional organizational links that the more experienced pilots do not have (overdefined concepts).

Comparison of Novice and Expert Pilots using GWN. We used the GWN algorithm to isolate those concepts and relations that distinguish expert fighter pilots from novices. These concepts and relations fall into two categories: (a) those that experts have that the novices do not and (b) those that novices have that experts do not. The undergraduate pilots served as the novice group, and the instructor and guard pilots were the experts.

In the organization of any set of concepts, there are a number of idiosyncratic relations in the network of any individual person or group of people. In order to avoid these idiosyncracies, the study focused on the group networks for expert and novice fighter pilots. We were interested in comparing the network derived from the UPT data against the representation of critical flight information.

Critical flight information was defined as the segments of the MEN that were shared by both groups of experts, i.e., the links contained in the MEN of both the IPs and the GPs. If the student network does not have a link found in both expert networks, the student may be missing a piece of critical flight information. Similarly, if the student has a link that is found neither in the IP network nor in the GP network, then the student may have a misconception about the relation between the linked concepts.

Critical flight network and assemblies. GWN found the MEN for the IPs and GPs. The intersection of these MENs formed the critical links of the expert pilots. As can be seen in Figure 16, this led to a disconnected network composed of three connected components and three concepts that did not have any critical links. These three concepts were connected to the IP and GP networks differently and thus do not produce any critical links. These concepts are good examples of the role of idiosyncratic information in the networks.

For each connected component, the DCs and accompanying assemblies were identified. Note that there were no critical cycles so a cycle analysis was not done. Table 28 lists the DCs and accompanying assemblies for each connected component. If a DC was also a terminal concept, we included that concept within the larger assembly for ease of exposition. The DCs for the critical network were: GUNS, CUTOFF, VERTICAL MANEUVERING, AIRSPEED, RELATIVE ENERGY, LAG ROLL, RADIAL G, 3-9 LINE. The Vertical Maneuvering Connected Component is partitioned into a Guns Subassembly, Angle Off subassembly, Vertical Maneuvering subassembly, and an Airspeed subassembly. In the Guns Subassembly, CUTOFF was also a DC as was RELATIVE ENERGY in the Airspeed Subassembly. The Lag Roll Subassembly forms with LAG ROLL as the center and RADIAL G and 3-9 LINE as terminal DCs. The Heat Component and Acceleration Component have only two concepts each and thus are not reducible to subassemblies. There is considerable similarity between the DCs and assemblies found for the IPs earlier and the critical DCs and assemblies found in this analysis.

The critical links in the assemblies are underlined. The three columns next to each link indicate whether the MEN for each of the three groups of pilots contained that link. For example, within the Guns Subassembly for the concept LEAD PURSUIT we find three links. Two of the links are critical and shared by the IPs and GPs (GUNS and CUTOFF), and one of the links is noncritical and held by only the students (OVERTAKE). A perusal of the table shows that some links are possessed by only one group, some links are shared by UPTs and IPs or by UPTs and GPs or by IPs and GPs (critical), and some links are shared by all (critical links held by the students).

Table 28

Assemblies for the Split-Plane Concepts

KEY:

The table (which appears on the following several pages) depicts links connected to concepts according to GWN solutions for student pilots, instructor pilots, and national guard pilots. Minimal elaborated networks were used for the students and guards, while an elaborated network with 51 links was used for the instructors in order to equate number of direct concept-to-concept links.

In the left-hand column, elements of the network are listed. The next column contains the elements that are linked to the elements listed in the first column. The X's indicate which pilot groups have that link.

Underlined concepts and corresponding X's represent critical links. A critical link is one that is in the network of both the instructors and guards.

ASSEMBLIES used critical links and were formed in the following ways:

1) A disconnected network was formed from the critical links and nodes.

2) Each connected component was labelled by its graph theoretic median (or if no relative median could be uniquely determined, one was chosen). This led to four connected components (i.e., VERTICAL MANEUVERING, LAG ROLL, HEAT, ACCELERATION) and three independent concepts (i.e., BARREL ROLL, OVERTAKE, LOW YO YO).

3) The minimal externally stable sets of maximally dominating concepts (MDC) were determined for each connected component and the set that was most internally stable was used to form subassemblies of the connected components.

(Table 28 continued)

VERTICAL MANEUVERING CONNECTED COMPONENTGUNS SUBASSEMBLY

		<u>UPTs</u>	<u>IPs</u>	<u>GPs</u>
GUNS (MDC)	<u>SWITCHOLOGY</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>SNAPSHOT</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>WEAPONS PARAMETERS</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>LEAD PURSUIT</u>		<u>X</u>	<u>X</u>
	6 O'CLOCK	X		
SWITCHOLOGY	<u>GUNS</u>	<u>X</u>	<u>X</u>	<u>X</u>
	HEAT		X	
SNAPSHOT (shared by angle off subassembly)	<u>GUNS</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>ANGLE OFF</u>		<u>X</u>	<u>X</u>
	3-9 LINE	X		
	BARREL ROLL	X		
	ASPECT ANGLE			X
	G LOADING			X
	OVERTAKE			X
WEAPONS PARAMETERS	<u>GUNS</u>	<u>X</u>	<u>X</u>	<u>X</u>
	EXTENSION	X		
	ASPECT ANGLE	X	X	
	LAG ROLL	X		
	ANGLE OFF	X		X
	RADIAL G	X		
	HEAT	X	X	
	G LOADING		X	
	6 O'CLOCK			X
	<u>HEAT ASSEMBLY</u>	<u>X</u>	<u>X</u>	<u>X</u>
LEAD PURSUIT	<u>GUNS</u>		<u>X</u>	<u>X</u>
	<u>CUTOFF</u>		<u>X</u>	<u>X</u>
	OVERTAKE	X		X
CUTOFF (MDC)	<u>LEAD PURSUIT</u>		<u>X</u>	<u>X</u>
	3-9 LINE	X		
	ASPECT ANGLE	X		X
	OVERTAKE	X	X	
	RELATIVE ENERGY			X
	ANGLE OFF			X
	LO YO YO		X	

(Table 28 continued)

<u>VERTICAL MANEUVERING SUBASSEMBLY</u>		<u>UPTs</u>	<u>IPs</u>	<u>GPs</u>
VERTICAL MANEUVERING (MDC) (shared by airspeed subassembly)	<u>HI YO YO</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>LIFT VECTOR</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>QUARTER PLANE</u>		<u>X</u>	<u>X</u>
	<u>AIRSPEED</u>		<u>X</u>	<u>X</u>
	<u>BARREL ROLL</u>	X	X	
	<u>RELATIVE ENERGY</u>	X		
	<u>3-9 LINE</u>			X
	<u>LAG ROLL</u>		X	
	<u>LAG ROLL ASSEMBLY</u>	<u>X</u>	<u>X</u>	<u>X</u>
HI YO YO	<u>VERTICAL MANEUVERING</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>LO YO YO</u>	<u>X</u>		
	<u>3-9 LINE</u>	X		
	<u>ASPECT ANGLE</u>	X		X
	<u>QUARTER PLANE</u>		X	
	<u>BARREL ROLL</u>			X
LIFT VECTOR	<u>VERTICAL MANEUVERING</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>QUARTER PLANE</u>	<u>X</u>		
	<u>G LOADING</u>	X		X
	<u>RADIAL G</u>		X	
	<u>LAG ROLL ASSEMBLY (G)</u>	<u>X</u>	<u>X</u>	<u>X</u>
QUARTER PLANE (shared by angle off subassembly)	<u>VERTICAL MANEUVERING</u>		<u>X</u>	<u>X</u>
	<u>ANGLE OFF</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>3-9 LINE</u>	<u>X</u>	<u>X</u>	
	<u>LIFT VECTOR</u>	X		
	<u>EXTENSION</u>	X		
	<u>ASPECT ANGLE</u>	X		X
	<u>LAG PURSUIT</u>	X	X	
	<u>LO YO YO</u>	X		
	<u>HI YO YO</u>		X	
	<u>RADIAL G</u>			X
	<u>6 O'CLOCK</u>		X	
	<u>LAG ROLL ASSEMBLY (3-9)</u>	<u>X</u>	<u>X</u>	<u>X</u>

(Table 28 continued)

		UPTs	IPs	CPs
<u>AIRSPD SUBASSEMBLY</u>				
AIRSPD (MDC) (shared by vertical maneuver subassembly)	SMASH	X	X	X
	CORNER VELOCITY	X	X	X
	PURE PURSUIT	X	X	X
	VERTICAL MANEUVERING		X	X
	POWER SETTING		X	X
	EXTENSION	X		X
	OVERTAKE	X		X
	ACCELERATION		X	
	LO YO YO			X
	ACCELERATION ASSEMBLY	X	X	X
SMASH	AIRSPD	X	X	X
	RELATIVE ENERGY	X	X	X
	HEAT	X		
	ACCELERATION	X		X
	OVERTAKE		X	
	POWER SETTING		X	
	EXTENSION		X	
	G LOADING		X	
	ACCELERATION ASSEMBLY	X	X	X
CORNER VELOCITY	AIRSPD	X	X	X
	G LOADING	X		X
PURE PURSUIT	AIRSPD	X	X	X
	6 O'CLOCK	X		X
	HEAT		X	
	ACCELERATION		X	
	RELATIVE ENERGY		X	
	HEAT ASSEMBLY	X	X	X
POWER SETTING	AIRSPD		X	X
	ACCELERATION	X		
	SMASH		X	
	EXTENSION		X	
RELATIVE ENERGY (MDC)	SMASH	X	X	X
	VERTICAL MANEUVERING	X		
	LAG PURSUIT	X		
	LO YO YO	X		
	LAG ROLL			X
	RADIAL G			X
	BARREL ROLL			X
	CUTOFF			X
	PURE PURSUIT		X	

(Table 28 continued)

<u>ANGLE OFF</u>	<u>SUBASSEMBLY</u>	<u>UPTs</u>	<u>IPs</u>	<u>GPs</u>
<u>ANGLE OFF</u>	<u>QUARTER PLANE</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>SNAPSHOT</u>		<u>X</u>	<u>X</u>
	WEAPONS PARAMETERS	X		X
	OVERTAKE	X		
	CUTOFF			X
	3-9 LINE			X
	LAG ROLL			X
	BARREL ROLL			X

(Table 28 continued)

<u>LAG ROLL CONNECTED COMPONENT</u>			
	<u>UPTs</u>	<u>IPs</u>	<u>GPs</u>
LAG ROLL (MDC)	<u>LAG PURSUIT</u>	<u>X</u>	<u>X</u>
	<u>ASPECT ANGLE</u>	<u>X</u>	<u>X</u>
	<u>G LOADING</u>	<u>X</u>	<u>X</u>
	RELATIVE ENERGY		X
	BARREL ROLL	X	
	3-9 LINE	X	
	WEAPONS PARAMETERS	X	
	ANGLE OFF		X
	VERTICAL MANEUVERING	X	
	<u>AIRSPPEED ASSEMBLY</u>	<u>X</u>	<u>X</u>
LAG PURSUIT	<u>LAG ROLL</u>	<u>X</u>	<u>X</u>
	<u>QUARTER PLANE</u>	<u>X</u>	
	RELATIVE ENERGY	X	
	RADIAL G	X	
	HEAT		
	BARREL ROLL		X
	6 O'CLOCK		X
	<u>HEAT ASSEMBLY</u>	<u>X</u>	<u>X</u>
ASPECT ANGLE	<u>LAG ROLL</u>	<u>X</u>	<u>X</u>
	<u>3-9 LINE</u>	<u>X</u>	<u>X</u>
	HI YO YO	X	X
	QUARTER PLANE	X	X
	CUTOFF	X	X
	WEAPONS PARAMETERS	X	
	BARREL ROLL		
	LO YO YO		X
	SNAPSHOT		X
	<u>GUNS ASSEMBLY</u>	<u>X</u>	<u>X</u>
G LOADING	<u>LAG ROLL</u>	<u>X</u>	<u>X</u>
	<u>RADIAL G</u>	<u>X</u>	<u>X</u>
	CORNER VELOCITY	X	X
	LIFT VECTOR	X	X
	ACCELERATION		X
	WEAPONS PARAMETERS		X
	SNAPSHOT		X
	BARREL ROLL		X
	EXTENSION		
	SMASH		
	<u>AIRSPPEED ASSEMBLY</u>	<u>X</u>	<u>X</u>
	<u>GUNS ASSEMBLY</u>	<u>X</u>	<u>X</u>

(Table 28 continued)

		<u>UPTs</u>	<u>IPs</u>	<u>GPs</u>
RADIAL G (MDC)	<u>G LOADING</u>	<u>X</u>	<u>X</u>	<u>X</u>
	WEAPONS PARAMETERS	<u>X</u>		
	LAG PURSUIT	<u>X</u>		
	BARREL ROLL	<u>X</u>		
	LIFT VECTOR		X	
	QUARTER PLANE			X
	RELATIVE ENERGY			X
	<u>VERTICAL ASSEMBLY</u>		<u>X</u>	<u>X</u>
	<u>ANGLE OFF ASSEMBLY</u>		<u>X</u>	<u>X</u>
3-9 LINE (MDC)	<u>ASPECT ANGLE</u>		<u>X</u>	<u>X</u>
	HI YO YO	X		
	QUARTER PLANE	X	X	
	LAG ROLL	X		
	CUTOFF	X		
	SNAPSHOT	X		
	VERTICAL MANEUVERING			X
	ANGLE OFF			X
	<u>VERTICAL ASSEMBLY</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>ANGLE OFF ASSEMBLY</u>	<u>X</u>	<u>X</u>	<u>X</u>

(Table 28 continued)

	<u>HEAT CONNECTED COMPONENT</u>		
	<u>UPTs</u>	<u>IPs</u>	<u>QPs</u>
HEAT	<u>6 O'CLOCK</u>	<u>X</u>	<u>X</u>
	WEAPONS PARAMETERS	X	
	SMASH	X	
	LAG PURSUIT	X	
	PURE PURSUIT	X	
	SWITCHOLOGY	X	
6 O'CLOCK	<u>HEAT</u>	<u>X</u>	<u>X</u>
	PURE PURSUIT	X	X
	GUNS	X	
	WEAPONS PARAMETERS		X
	LAG PURSUIT		X
	QUARTER PLANE	X	
	<u>VERTICAL/AIRSPD ASSEMB.</u>	<u>X</u>	<u>X</u>

<u>ACCELERATION CONNECTED COMPONENT</u>			
ACCELERATION	<u>EXTENSION</u>	<u>X</u>	<u>X</u>
	SMASH	X	X
	POWER SETTING	X	
	LO YO YO		X
	AIRSPD		X
	G LOADING		X
	OVERTAKE		X
	PURE PURSUIT		X
	<u>AIRSPD ASSEMBLY</u>	<u>X</u>	<u>X</u>
EXTENSION	<u>ACCELERATION</u>	<u>X</u>	<u>X</u>
	QUARTER PLANE	X	
	AIRSPD	X	X
	WEAPONS PARAMETERS	X	
	POWER SETTING		X
	SMASH		X
	G LOADING		X
	<u>AIRSPD ASSEMBLY</u>	<u>X</u>	<u>X</u>

(Table 28 concluded)

		<u>INDEPENDENT CONCEPTS</u>		
		<u>UPTs</u>	<u>IPs</u>	<u>GPs</u>
BARREL ROLL	LAG ROLL	X		
	RADIAL G	X		
	SNAPSHOT	X		
	VERTICAL MANEUVERING	X	X	
	ASPECT ANGLE		X	
	ANGLE OFF			X
	G LOADING			X
	RELATIVE ENERGY			X
	LAG PURSUIT			X
	HI YO YO			X
	<u>VERTICAL ASSEMBLY</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>LAG ASSEMBLY</u>	<u>X</u>	<u>X</u>	<u>X</u>
OVERTAKE	AIRSPEED	X		X
	ANGLE OFF	X		
	CUTOFF	X	X	
	LEAD PURSUIT	X		X
	SMASH		X	
	SNAPSHOT			X
	ACCELERATION		X	
	<u>GUNS ASSEMBLY (CUTOFF)</u>	<u>X</u>	<u>X</u>	<u>X</u>
	<u>AIRSPEED ASSEMBLY</u>	<u>X</u>	<u>X</u>	<u>X</u>
LO YO YO	HI YO YO	X		
	QUARTER PLANE	X		
	RELATIVE ENERGY	X		
	ACCELERATION		X	
	AIRSPEED			X
	ASPECT ANGLE			X
	CUTOFF		X	
	<u>AIRSPEED/ACCEL. MACRO.</u>		<u>X</u>	<u>X</u>

Table 28 also reveals connections from concepts to assemblies. To connect from a concept to an assembly requires only a link from that concept to any concept in that assembly. For example, WEAPONS PARAMETERS has a critical link to the Heat Assembly. This means that while IPs and GPs did not agree on the direct link emanating from WEAPONS PARAMETERS, they did agree that there should be some connection from WEAPONS PARAMETERS to the assembly of concepts dealing with Heat. In this specific example, the MEN for IPs had a WEAPONS PARAMETERS to HEAT link while the GPs had a link between WEAPONS PARAMETERS and 6 O'CLOCK. Since HEAT and 6 O'CLOCK belong to the same assembly, a link is added to that assembly. This is incidentally a critical link that the UPTs also have.

Table 28 permits the classification of concepts along two dimensions: underdefinition and overdefinition. Underdefined concepts for UPTs are those that are missing a large proportion of critical links. Overdefined concepts are those that the UPTs have connected to the network using links that neither the IPs nor the GPs have in their networks. We determined the probability of a UPT having a link given that the link was critical as well as the probability of the UPTs having a link given that neither experienced pilot group had the link. We then did a median split on each dimension and classified the concepts as to whether they were high on both dimensions, low on both dimensions, or high on one and low on the other. This leads to four classes of concepts: well defined, over defined, under defined, and misdefined. These concepts appear in Table 29. The actual links involved in the classification of these concepts appear in Table 30.

The critical links not held by the UPTs are those relations found in the conceptual structure of experienced pilots but not in that of the students. Some of the structure missing in the student networks are concept-to-concept links (e.g., VERTICAL MANEUVERING--QUARTER PLANE) whereas others are concept-to-assembly links (e.g., LAG PURSUIT--HEAT ASSEMBLY). Recall that if a student is missing a critical concept-to-assembly link, the MEN for the UPTs does not contain a link from that concept to any concept in that assembly. For some concepts, the UPTs have none of the critical relations: LEAD PURSUIT, HEAT, and LOW YO YO. In fact, for LEAD PURSUIT, the UPTs show no link to any concept in the Guns Subassembly to which it belongs. Two other critical relations shown in Table 30 are worth highlighting here. Both the VERTICAL MANEUVERING--QUARTER PLANE and the ACCELERATION--EXTENSION relations are highly discriminating relations according to the pattern classification analysis discussed earlier. The fact that these two relations are critical (according to the GWN analysis) and the fact that they are important in discriminating between novice and experienced pilots (according to the pattern classification analysis) provide convergent validation that these relations are important parts of an expert's organization of flight information that is lacking in that of the novice.

Table 29

Comparison of Novice and Expert Concepts

Well-Defined Concepts

GUNS
G LOADING
AIRSPEED

PURE PURSUIT
LIFT VECTOR
OVERTAKE

SWITCHOLOGY
6 O'CLOCK
CORNER VELOCITY

Over-Defined Concepts (Compare Table 30)

SNAPSHOT
VERTICAL MANEUVERING
BARREL ROLL
LAG PURSUIT
EXTENSION

WEAPONS
HI YO YO
SMASH
3-9 LINE
LO YO YO

ANGLE OFF
QUARTER PLANE
RELATIVE ENERGY
ACCELERATION

Under-Defined Concepts (Compare Table 30)

LEAD PURSUIT
ASPECT ANGLE

CUTOFF
HEAT

POWER SETTING

Misdefined Concepts

LAG ROLL

RADIAL G

Table 30

Differences in Concept Links for Novices and Experts

Critical Expert Links not in Novice Network
(Underdefined Concepts)

GUN3-LEAD PURSUIT	SNAPSHOT-ANGLE OFF
CUTOFF-LEAD PURSUIT	VERTICAL MANEUVERING-QUARTER PLANE
VERTICAL MANEUVERING-AIRSPED	AIRSPED-POWER SETTING
LAG ROLL-ASPECT ANGLE	LAG ROLL-G LOADING
LAG ROLL-AIRSPED ASSEMBLY	LAG PURSUIT-HEAT ASSEMBLY
ASPECT ANGLE-3/9 LINE	G LOADING-GUNS ASSEMBLY
RADIAL G-VERTICAL ASSEMBLY	RADIAL G-ANGLE OFF ASSEMBLY
HEAT-6 O'CLOCK	ACCELERATION-EXTENSION
LO YO YO-AIRSPED/ACCELERATION	
MACROASSEMBLY	

Links in the Novice Network not found for Experts
(Overdefined Concepts)

GUNS-6 O'CLOCK	3/9 LINE-SNAPSHOT
BARREL ROLL-SNAPSHOT	WEAPONS PARAMETERS-EXTENSION
WEAPONS PARAMETERS-LAG ROLL	WEAPONS PARAMETERS-RADIAL G
WEAPONS PARAMETERS-G LOADING	CUTOFF-3/9 LINE
ANGLE OFF-OVERTAKE	VERTICAL MANEUVERING-RELATIVE ENERGY
HI YO YO-LO YO YO	HI YO YO- 3/9 LINE
LIFT VECTOR-QUARTER PLANE	QUARTER PLANE-EXTENSION
QUARTER PLANE-ASPECT ANGLE	QUARTER PLANE-LO YO YO
SMASH-HEAT	POWER SETTING-ACCELERATION
RELATIVE ENERGY-LAG PURSUIT	RELATIVE ENERGY-LO YO YO
LAG ROLL-BARREL ROLL	LAG ROLL-3/9 LINE
LAG PURSUIT-RADIAL G	RADIAL G-BARREL ROLL

Perhaps as serious as not having the correct relations is having inappropriate relations. The overdefined concepts are those that the students have connected to the network in a fashion that is different from either group of experienced pilots. For some concepts, this overdefinition is quite severe: WEAPONS PARAMETERS, QUARTER PLANE, and 3-9 LINE. In fact, for QUARTER PLANE, 19% (4/21) of those relations not found in an experienced pilot's network are included in the UPT structure. One other inappropriate relation is worth highlighting. The pattern classification procedures suggest that this relationship is highly discriminating, and the network analysis suggests that it is important to the UPT structure: HIGH YO YO--LOW YO YO. Apparently the similarity between HIGH and LOW YO YO is in name only for the experienced pilots, yet the UPTs have that as a direct concept-to-concept link in their network.

Finally, two concepts did not include many of the critical links and, in addition, included many extraneous links. In this sense, LAG ROLL and RADIAL G were both underdefined and overdefined, but more appropriately we have termed them misdefined. For LAG ROLL, the UPTs do not have critical links to ASPECT ANGLE, G LOADING, nor any link to the AIRSPEED SUBASSEMBLY. Instead they do have extraneous links from LAG ROLL to BARREL ROLL, 3-9 LINE, and WEAPONS PARAMETERS. Similarly, for RADIAL G the UPTs have no critical connections to any concept in either the VERTICAL SUBASSEMBLY or the ANGLE OFF ASSEMBLY, but do have extraneous links to WEAPONS PARAMETERS, LAG PURSUIT, and BARREL ROLL.

This phase of the project has highlighted those concepts and relations that the UPTs have not as yet mastered. The emphasis on differences between the UPTs and expert pilots should not be taken as indicative of the progress of the UPTs. In fact, their overall correspondence with the IPs, and especially with the GPs, is quite high. Several concepts are quite well mastered while several others are only slightly (1 link) different from the more experienced pilots.

The use of general networks and the GWN algorithm holds substantial promise in attempts to specify the local relations and structure present in the conceptual organization of critical flight information. In addition, it allows a detailed, concept-by-concept, comparison across groups that differ in expertise. The use of networks coupled with other techniques, especially MDS and pattern classification, should provide valid, usable information in a form that could be incorporated into the training procedures of fighter pilots.

GENERAL DISCUSSION

Primary Accomplishments

This project has produced several interesting and potentially useful findings. The major new theoretical contribution lies in the development of methods for obtaining and analyzing networks of concepts. This method should contribute to the continued development of an understanding of structures and processes in semantic memory.

In the domain of critical flight-related concepts, we have shown that systematic methods can yield valid and reliable descriptions of the structure of these concepts. Further, these structures can be used to identify individuals as members of groups with different training and experience. We have also identified some specific areas of disagreement in the structures possessed by expert and novice pilots. These specific differences may deserve special attention in lead-in fighter training. The structures themselves may also prove to be useful in the academic program since they provide some graphic examples of the differences in the ways novices and experts think about critical flight concepts.

In the context of the ongoing effort in this contract, this first contract period has resulted in several analytical methods with which to pursue experimental analysis of conceptual structures in fighter pilots. While much of the initial effort has been concerned with measurement issues, it has been necessary to define and validate the basic purpose of the contract. The work in the initial period has also led to several structural analyses that serve to define structures of memory for critical flight information. We now have a firm foundation on which to build further work. While we intend to continue to investigate the problems associated with representing knowledge, the next contract period will include experimental investigations of the structures we have already established.

Utility and Limitations of Particular Structural Analyses

In this project, several techniques have been applied for obtaining structural representations of critical flight information. We began by applying traditional scaling techniques, such as multi-dimensional scaling and hierarchical clustering analysis to psychological distances derived from similarity ratings. We then developed a new structuring technique, general weighted networks, and applied it to the same similarity data. Though the resulting critical flight structures point to a number of similar conclusions, they do differ in a number of ways. Consideration of these differences in light of the current interest in fighter pilot conceptual memory will allow the important details to be abstracted from each structure. These details can be used to gain an understanding of critical flight information that could not be gleaned from any single structural representation. We believe that the appropriate use of all structural representations

is the most sensible way to proceed in attempting to understand any organized conceptual domain. It is a particularly rational approach in attempting to understand conceptual domains that have been subjected to almost no prior analysis, as is the case with critical flight information.

Consider first the results of the Multidimensional Scaling (MDS) procedures. MDS took as input a set of empirical psychological distances and produced a set of derived distances. The derived distances contained metric properties that were not present in the empirical judgments. The fact that this metric information is quite useful is highlighted by the consistent improvement in correlations found with distances compared to empirical ratings and in the more successful pattern classification found with the MDS distances. The constraints that MDS places on the distances are quite severe (e.g., the formation of isosceles triangles) and thus results in both very useful and very misleading information in the structures. The useful information appears in the form of global properties of the structure. For example, only MDS can abstract dimensions from the rating data, but it can produce local distortions in the distances between particular pairs of concepts.

With MDS, solutions of moderate dimensionality were obtained for each of the subject groups. Provided that the dimensions produced in the solution can be identified, these dimensions can provide a great deal of information about the underlying characteristic features of the conceptual domain. For example, the fact that a temporal sequencing seems to pervade these domains is obviously critical to the understanding of the structure. The temporal dimension serves as a good example of both a strength and weakness of multidimensional scaling solutions. No other scaling solution could have shown this continuous feature of the structure. Thus, MDS is unsurpassed in its ability to point out important underlying continuous dimensions of variation in the concepts. Alternatively, if the underlying dimension is discrete then the MDS solution is less than optimal and should be used in conjunction with one of the other scaling procedures. So, though the metric properties of an MDS solution allows for the abstraction of dimensions, a boundary condition on the usefulness of this global feature of MDS is that the dimension be continuous.

Though the MDS metric places points in an N dimensional space and allows for the identification of continuous dimensions, the metric requires a certain sacrifice to accomplish this. The sacrifice is in terms of local distortions in the structure which prevent an analysis of the subcomponents of the MDS structure. Hierarchical Clustering (HC) analysis and General Weighted Networks (GWN) focus on these local relationships, though they provide less global information than does MDS.

HC transforms the empirical ratings into a set of classes. A concept within a cluster is more related to another member of the cluster than to a concept from another cluster. Comparing an HC solution with an MDS solution for the same data helps point out some of the distortions that MDS makes in the local structure. Two items close together in multidimensional space may not cluster together while two items distant in space may cluster together. Figure 17 shows an HC solution superimposed on a two dimensional space of split-plane concepts for IPs.

HC requires that a concept belong to one and only one cluster though that cluster as a whole may belong to a larger, in a sense superordinate, cluster. This hierarchical constraint also results in some distortions in the structure since many concepts do not exist with one another in a hierarchical relationship. Another problem with using HC as a means for determining local relations is that there is no a priori way to partition the tree to allow finer grained analyses. Though the trees for UPTs and IPs were partitioned into five major clusters, this could have easily been four or seven. General weighted networks provide a better vehicle for determining local relations. However, HC does produce free nodes in its solution (unlabelled nodes in the tree) that GWN does not produce in its present form. These free nodes may be valuable if one wished to determine hierarchical relations, though they are often difficult to label. The GWN does not distinguish between hierarchical and nonhierarchical relations without some a priori knowledge of the relationship between concepts. However, MDS, HC, and GWN are not typically applied to random collections of concepts; rather the user typically brings intuition to bear on the establishment of the conceptual domain. Thus there is no apparent benefit of HC over GWN for establishing local relations within a conceptual structure.

GWN also takes psychological distance data as input and produces a conceptual structure in the form of a network. Currently, the network mirrors the original ratings rather than transforming them in any way. This has the advantage of staying close to the data base and, thus, not introducing distortion into the links. However, there is distortion in chains of links in that the original ratings do not correspond to the length of a chain. Future work will focus on improving the metric properties of GWN.

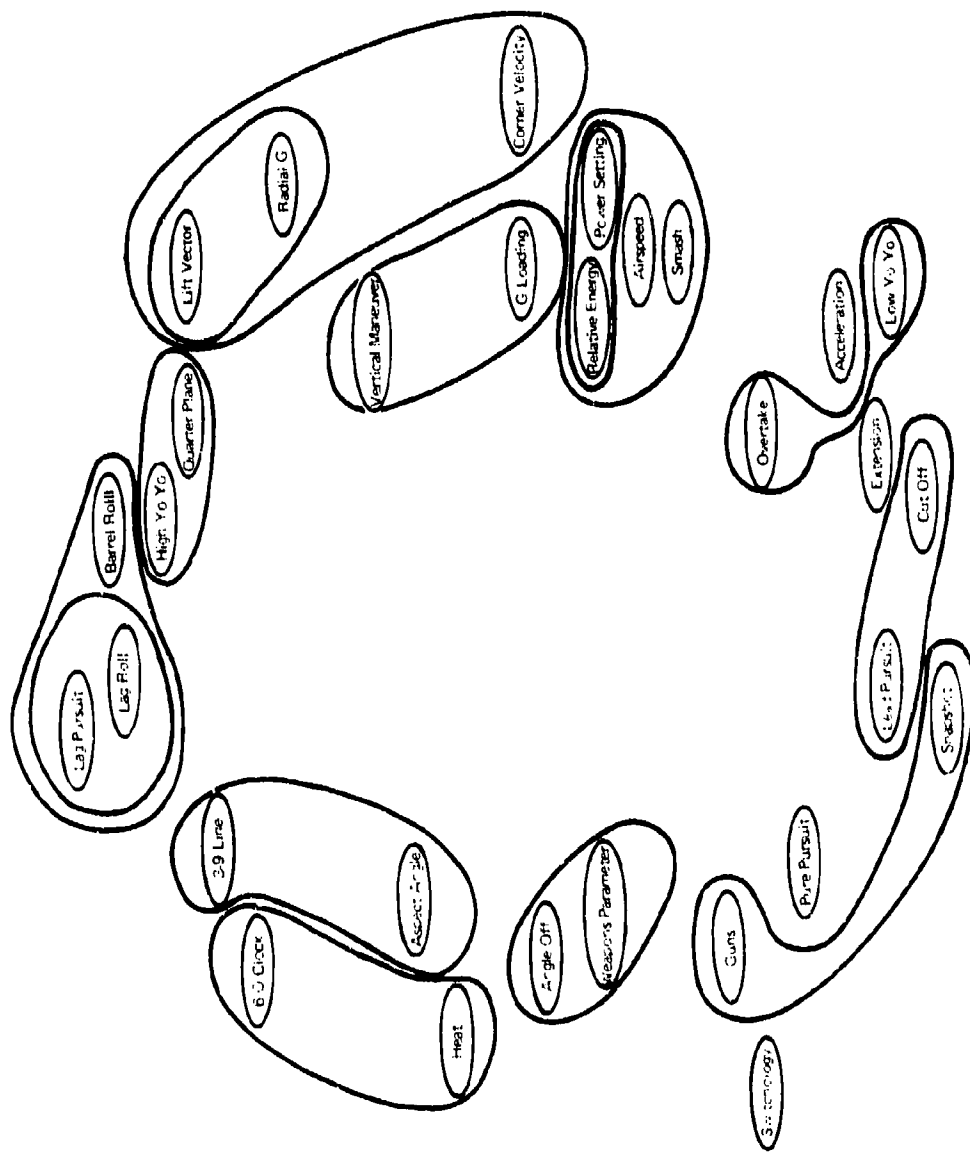


Figure 17. Hierarchical Clustering solution imposed on a 2-D MDS solution. Concepts enclosed in loops cluster together. Some nearby concepts do not cluster and some distant concepts do cluster.

Networks have a number of properties that allow for a better understanding of conceptual structures. Unlike MDS, networks focus on the local relations of the structure. In this sense, it is similar to HC. Networks allow multiple connections within the structure and thus allow one to partition the network into assemblies and cycles. As has been shown in this report, assemblies and cycles form meaningful units that aid in the understanding of the overall network. In addition, cycles and assemblies allow a comparison across groups of individuals on a concept-by-concept basis: a task that is difficult or impossible to do with the more traditional scaling procedures. Finally, networks are weighted and this distance information can be used to form minimum cycles, determine the concept in the network that is closest to all other concepts (median), or determine the concept that allows the most rapid connection to the most distant concept (center). Though these last two properties are more interpretable in a metricized network, their potential for summarizing networks and differences among networks can be quite useful. Finally, networks potentially allow concepts as well as links to be weighted. More important concepts or more "costly" concepts could be weighted in such a way as to make some concepts more critical than others. As GWN now stands, it provides a great deal of information about the local structure of conceptual domains and, with the addition of a metric, will introduce a number of other features that will aid in understanding critical flight information. We believe that the results of GWN, coupled with the global characteristics gleaned from MDS analyses, should provide the best understanding of the structure of critical flight information.

Directions for Future Work

One major area to be pursued in future work concerns the experimental verification of the structures we have identified. We intend to pursue this goal with priming methodology and recognition memory experiments. We are also proceeding with the analysis of memory in the form of scripts and frames. It would also be useful to pursue the predictive power of these techniques by systematically following individual UPTs through training. Perhaps individuals could be identified who would most benefit from fighter training.

The network algorithm should be developed further. It should be possible to develop a metric based on the network that could lead to some experimental comparisons of the MDS metric and the GWN metric. While the network itself is produced by an algorithm, more work is needed to develop algorithms for defining cycles and assemblies in the networks. In short, the network representation is most promising, and additional efforts will be required for the network analysis to reach its full potential.

Further detailed analysis of the concepts from the low-angle strafe maneuver could be performed along the same lines as that presented here for the split-plane maneuvers. Also, another group of students who have completed fighter lead-in training should be obtained to permit an analysis of the effects of training in the specific maneuvers represented by our stimulus materials.

Recommendations

The research presented in this report provides a detailed analysis of the conceptual structure of critical flight information in fighter pilots. As such, the structures should be of use in designing training programs for students attempting to acquire these conceptual structures. In addition, the representations themselves may prove to be useful as training aids. The network analysis, for example, shows how expert fighter pilots organize the concepts involved in particular maneuvers. To the extent that the network representation provides an understandable representation of experts' knowledge structures, students may find it useful in learning about the maneuvers.

From a somewhat different angle, we have identified specific differences in the conceptual structures of students and expert fighter pilots. In particular, the differences show, in part, what experts know that students do not and what misconceptions the students may have acquired from earlier training or from other life experiences. These areas of difference should receive special attention in the training program for fighter pilots.

Finally, our work in classifying individuals based on their conceptual structure suggests further work in attempting to predict the success of future fighter pilots based on the conceptual structures students demonstrate early on in training. It may be necessary to study the structures associated with a different set of concepts than those used in the present investigation. For example, perhaps some concepts relating to attitude and motivation should be included along with concepts relating to the operation of aircraft. The classification techniques we have developed appear to be very sensitive to differences in cognitive structures, and they may well provide some predictive power for organizing the training program to produce maximum benefit for those who are likely to benefit the most from fighter training.

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APPENDIX

The tables in the appendix present the detailed inter-individual correlations for both rating scores and MDS distances. Both the split-plane concepts and the low-angle strafe concepts are represented.

Split-Plane Manuevers

Inter-Individual Correlation Matrix

I1 through I7 are individual instructor pilots

Rating Scores

	I1	I2	I3	I4	I5	I6	I7
I1	-	.35	.47	.45	.42	.58	.43
I2	.35	-	.41	.41	.47	.38	.32
I3	.47	.41	-	.49	.43	.42	.43
I4	.45	.41	.49	-	.41	.43	.41
I5	.42	.47	.43	.41	-	.42	.41
I6	.58	.38	.42	.43	.42	-	.37
I7	.43	.32	.43	.41	.41	.37	-

Mean Correlation = .42

Distances in Multidimensional Space

	I1	I2	I3	I4	I5	I6	I7
I1	-	.34	.53	.50	.45	.57	.47
I2	.34	-	.41	.40	.43	.35	.38
I3	.53	.41	-	.59	.47	.44	.52
I4	.50	.40	.59	-	.41	.51	.51
I5	.45	.43	.47	.41	-	.41	.49
I6	.57	.35	.44	.51	.41	-	.37
I7	.47	.38	.52	.51	.49	.37	-

Mean Correlation = .45

Split-Plane Maneuvers

Inter-Individual Correlation Matrix

G1 through G9 are individual guard pilots

Rating Scores

	G1	G2	G3	G4	G5	G6	G7	G8	G9
G1	-	.44	.42	.32	.30	.37	.34	.38	.36
G2	.44	-	.40	.36	.42	.43	.51	.43	.36
G3	.42	.40	-	.33	.29	.40	.43	.31	.39
G4	.32	.36	.33	-	.32	.38	.25	.42	.33
G5	.30	.42	.29	.32	-	.38	.31	.29	.33
G6	.37	.43	.40	.38	.38	-	.30	.46	.36
G7	.34	.51	.43	.25	.31	.30	-	.33	.38
G8	.38	.43	.31	.42	.29	.46	.33	-	.25
G9	.36	.36	.39	.33	.33	.36	.38	.25	-

Mean Correlation = .36

Distances in Multidimensional Space

	G1	G2	G3	G4	G5	G6	G7	G8	G9
G1	-	.40	.47	.37	.32	.34	.39	.38	.37
G2	.40	-	.47	.42	.41	.41	.50	.40	.38
G3	.47	.47	-	.42	.32	.43	.54	.33	.50
G4	.37	.42	.42	-	.35	.43	.35	.41	.38
G5	.32	.41	.32	.35	-	.32	.38	.27	.33
G6	.34	.41	.43	.43	.32	-	.34	.45	.36
G7	.39	.50	.54	.35	.38	.34	-	.32	.47
G8	.38	.40	.33	.41	.27	.45	.32	-	.29
G9	.37	.38	.50	.38	.33	.36	.47	.29	-

Mean Correlation = .39

Split-plane Manuevers
Inter-Individual Correlation Matrix
U1 through U17 are individual undergraduate pilots

U1 U2 U3 U4 U5 U6 U7 U8 U9 U10 U11 U12 U13 U14 U15 U16 U17

Rating Scores

U1	-	.31	.24	.29	.37	.30	.14	.28	.44	.34	.36	.40	.31	.44	.35	.29	.24
U2	.31	-	.26	.32	.26	.25	.12	.21	.34	.30	.34	.29	.26	.36	.28	.28	.28
U3	.24	.26	-	.32	.37	.31	.26	.44	.37	.29	.44	.36	.35	.38	.27	.30	.23
U4	.29	.32	.32	-	.39	.30	.12	.30	.45	.33	.47	.29	.30	.49	.27	.35	.28
U5	.37	.26	.37	.39	-	.20	.22	.28	.42	.24	.38	.41	.26	.52	.27	.29	.30
U6	.30	.25	.31	.30	.20	-	.25	.34	.33	.24	.30	.26	.29	.35	.25	.18	.28
U7	.14	.12	.26	.12	.22	.25	-	.24	.28	.30	.30	.34	.30	.32	.17	.23	.28
U8	.28	.21	.44	.30	.28	.34	.24	-	.36	.26	.43	.24	.41	.36	.22	.19	.21
U9	.44	.34	.37	.45	.42	.33	.28	.36	-	.37	.43	.34	.36	.46	.31	.30	.29
U10	.34	.30	.29	.33	.24	.24	.30	.26	.37	-	.34	.36	.31	.36	.30	.27	.26
U11	.36	.34	.44	.47	.38	.30	.30	.43	.43	.34	-	.36	.43	.43	.38	.32	.29
U12	.40	.29	.36	.29	.41	.26	.34	.24	.34	.36	.36	-	.32	.47	.31	.29	.27
U13	.31	.26	.35	.30	.26	.29	.30	.41	.36	.31	.43	.32	-	.39	.29	.29	.29
U14	.44	.36	.38	.49	.52	.35	.32	.36	.46	.36	.43	.47	.39	-	.33	.35	.35
U15	.35	.28	.27	.27	.27	.25	.17	.22	.31	.30	.38	.31	.29	.33	-	.18	.26
U16	.29	.28	.30	.35	.29	.18	.23	.19	.30	.27	.32	.29	.29	.35	.18	-	.34
U17	.24	.28	.23	.28	.30	.28	.28	.21	.29	.26	.29	.27	.29	.35	.26	.34	-

Mean Correlation = .31

Distances in Multidimensional Space

U1	-	.33	.28	.28	.33	.27	.24	.31	.46	.39	.39	.30	.29	.43	.30	.32	.26
U2	.33	-	.27	.27	.18	.22	.18	.19	.34	.28	.29	.24	.29	.36	.26	.31	.26
U3	.28	.27	-	.33	.35	.27	.25	.38	.38	.32	.41	.28	.33	.31	.26	.33	.21
U4	.28	.27	.33	-	.27	.16	.12	.27	.36	.34	.39	.24	.33	.41	.26	.29	.29
U5	.33	.18	.35	.27	-	.17	.10	.31	.27	.22	.32	.26	.22	.44	.25	.23	.25
U6	.27	.22	.27	.16	.17	-	.29	.29	.35	.19	.23	.22	.27	.36	.21	.15	.25
U7	.24	.18	.25	.12	.10	.29	-	.20	.29	.33	.32	.23	.28	.25	.13	.30	.27
U8	.31	.19	.38	.27	.31	.29	.20	-	.35	.29	.42	.21	.35	.35	.29	.21	.19
U9	.46	.34	.38	.36	.27	.35	.29	.35	-	.38	.42	.28	.34	.47	.33	.28	.31
U10	.39	.28	.32	.34	.22	.19	.33	.29	.38	-	.41	.24	.31	.32	.37	.30	.28
U11	.39	.29	.41	.39	.32	.23	.32	.42	.42	.41	-	.21	.43	.35	.38	.25	.26
U12	.30	.24	.28	.24	.26	.22	.23	.21	.28	.24	.21	-	.15	.37	.20	.24	.26
U13	.29	.29	.33	.33	.22	.27	.28	.35	.34	.31	.43	.15	-	.40	.26	.29	.26
U14	.43	.36	.31	.41	.44	.36	.25	.35	.47	.32	.35	.37	.40	-	.28	.35	.43
U15	.30	.26	.26	.26	.25	.21	.13	.29	.33	.37	.38	.20	.26	.28	-	.14	.28
U16	.32	.31	.33	.29	.23	.15	.30	.21	.28	.30	.25	.24	.29	.35	.14	-	.28
U17	.26	.26	.21	.29	.25	.25	.27	.19	.31	.28	.26	.26	.26	.43	.28	.28	-

Mean Correlation = .29

Split-Plane Manuevers

Inter-Individual Correlation Matrix

W1 through W4 are individual IWSOs

Rating Scores

	W1	W2	W3	W4
W1	-	.45	.42	.40
W2	.45	-	.24	.28
W3	.42	.24	-	.50
W4	.40	.28	.50	-

Mean Correlation = .38

Distances in Multidimensional Space

	W1	W2	W3	W4
W1	-	.36	.46	.45
W2	.36	-	.24	.23
W3	.46	.24	-	.53
W4	.45	.23	.53	-

Mean Correlation = .38

Split-Plane Maneuvers

Inter-Individual Correlation between Guard and Instructor Pilots

G1 through G9 are individual guard pilots
I1 through I7 are individual instructor pilots

Rating Scores

	G1	G2	G3	G4	G5	G6	G7	G8	G9
I1	.38	.42	.48	.38	.32	.34	.38	.42	.34
I2	.36	.33	.35	.21	.25	.24	.31	.16	.25
I3	.40	.41	.39	.30	.30	.28	.42	.32	.44
I4	.38	.39	.41	.31	.37	.33	.42	.28	.35
I5	.38	.36	.44	.27	.24	.29	.39	.26	.45
I6	.34	.31	.40	.29	.24	.32	.30	.28	.32
I7	.39	.46	.43	.37	.36	.35	.48	.25	.43

Mean Correlation = .35

Distances in Multidimensional Space

	G1	G2	G3	G4	G5	G6	G7	G8	G9
I1	.38	.40	.50	.44	.36	.39	.44	.36	.39
I2	.37	.31	.36	.30	.29	.27	.39	.23	.40
I3	.42	.45	.47	.29	.35	.30	.48	.30	.50
I4	.41	.39	.45	.33	.38	.30	.45	.24	.42
I5	.32	.36	.48	.27	.25	.32	.41	.25	.50
I6	.37	.33	.41	.32	.25	.31	.28	.28	.32
I7	.42	.51	.52	.40	.36	.35	.49	.29	.46

Mean Correlation = .37

Split-Plane Manuevers

Inter-Individual Correlations for IPs and UPTs

I1 through I7 are individual instructor pilots
U1 through U17 are individual undergraduate pilots

	I1	I2	I3	I4	I5	I6	I7
	<u>Rating Scores</u>						
U1	.23	.20	.16	.26	.13	.16	.29
U2	.18	.06	.10	.18	.13	.13	.16
U3	.31	.22	.26	.34	.29	.22	.26
U4	.23	.14	.15	.26	.16	.23	.23
U5	.15	.16	.15	.25	.23	.09	.17
U6	.26	.11	.17	.29	.19	.17	.25
U7	.12	.10	.21	.30	.17	.06	.24
U8	.25	.06	.11	.25	.18	.20	.24
U9	.30	.18	.18	.32	.17	.19	.25
U10	.16	.12	.13	.25	.19	.09	.20
U11	.33	.16	.21	.30	.31	.21	.32
U12	.13	.19	.18	.23	.23	.07	.25
U13	.24	.17	.14	.21	.19	.16	.32
U14	.31	.19	.19	.32	.22	.21	.29
U15	.24	.13	.10	.24	.23	.19	.35
U16	.34	.17	.31	.31	.23	.30	.28
U17	.16	.11	.09	.27	.19	.21	.16

Mean Correlation = .20

	<u>Distance in Multidimensional Space</u>						
U1	.26	.25	.17	.24	.21	.24	.27
U2	.21	.08	.11	.12	.17	.12	.18
U3	.31	.24	.25	.29	.29	.20	.31
U4	.21	.17	.13	.24	.20	.23	.24
U5	.10	.19	.11	.17	.21	.13	.15
U6	.25	.16	.22	.27	.21	.19	.28
U7	.22	.21	.20	.29	.22	.13	.29
U8	.27	.16	.17	.25	.26	.20	.29
U9	.34	.18	.20	.34	.24	.22	.28
U10	.19	.16	.11	.19	.18	.15	.27
U11	.28	.19	.20	.23	.32	.21	.27
U12	.22	.26	.21	.20	.25	.14	.21
U13	.23	.15	.16	.20	.23	.15	.32
U14	.37	.29	.24	.32	.30	.29	.29
U15	.18	.17	.10	.21	.20	.21	.26
U16	.30	.22	.31	.26	.26	.26	.30
U17	.14	.23	.09	.30	.27	.20	.16

Mean Correlation = .22

Split-Plane Manuevers

Inter-Individual Correlation Matrix for Instructor Pilots and Instructor Weapons Systems Officers

I1 through I7 are individual instructor pilots
W1 through W4 are individual IWSOs

Rating Scores

	I1	I2	I3	I4	I5	I6	I7
W1	.37	.37	.41	.40	.45	.38	.38
W2	.21	.40	.30	.22	.38	.20	.26
W3	.39	.35	.42	.49	.43	.37	.48
W4	.46	.40	.54	.48	.42	.48	.47

Mean Correlation = .39

Distance in Multidimensional Space

	I1	I2	I3	I4	I5	I6	I7
W1	.41	.34	.43	.42	.43	.43	.42
W2	.09	.31	.22	.15	.26	.15	.21
W3	.44	.42	.54	.53	.50	.44	.55
W4	.54	.45	.55	.50	.47	.51	.53

Mean Correlation = .40

Split-Plane Manuevers

Inter-Individual Correlation Matrix for GPs and UPTs

G1 through G9 are individual Guard pilots
U1 through U17 are individual Undergraduate pilots

	G1	G2	G3	G4	G5	G6	G7	G8	G9
	<u>Rating Scores</u>								
U1	.19	.17	.19	.21	.28	.22	.17	.21	.21
U2	.24	.23	.18	.29	.15	.26	.18	.28	.12
U3	.23	.33	.29	.35	.29	.28	.30	.30	.21
U4	.17	.24	.19	.26	.26	.25	.13	.26	.21
U5	.09	.21	.19	.21	.19	.22	.13	.20	.15
U6	.23	.21	.29	.30	.21	.23	.18	.30	.23
U7	.15	.27	.22	.27	.29	.22	.23	.09	.17
U8	.18	.24	.26	.28	.19	.15	.19	.28	.21
U9	.23	.26	.29	.28	.28	.31	.22	.28	.21
U10	.19	.26	.19	.25	.26	.28	.16	.20	.19
U11	.27	.31	.27	.38	.36	.33	.28	.35	.34
U12	.15	.24	.25	.26	.29	.23	.16	.14	.18
U13	.31	.28	.30	.29	.25	.27	.22	.22	.21
U14	.17	.23	.27	.35	.30	.32	.23	.25	.20
U15	.29	.23	.25	.29	.28	.26	.20	.23	.24
U16	.20	.40	.29	.29	.26	.28	.28	.29	.26
U17	.14	.20	.22	.28	.16	.22	.16	.18	.18

Mean Correlation = .24

	<u>Distances in Multidimensional Space</u>								
U1	.24	.19	.22	.24	.27	.23	.32	.27	.25
U2	.21	.23	.13	.24	.16	.20	.23	.23	.10
U3	.21	.32	.31	.32	.28	.32	.32	.30	.22
U4	.22	.28	.18	.24	.23	.25	.14	.29	.17
U5	.13	.12	.19	.17	.15	.21	.17	.16	.09
U6	.25	.20	.33	.37	.20	.24	.23	.27	.22
U7	.15	.30	.28	.33	.32	.22	.31	.16	.25
U8	.21	.27	.23	.32	.17	.15	.23	.33	.19
U9	.30	.24	.28	.27	.23	.27	.30	.24	.22
U10	.25	.28	.25	.33	.26	.25	.28	.28	.24
U11	.28	.28	.25	.33	.39	.30	.32	.36	.24
U12	.18	.21	.22	.26	.16	.17	.22	.11	.19
U13	.23	.27	.23	.28	.23	.29	.26	.25	.12
U14	.22	.25	.27	.38	.28	.28	.28	.28	.22
U15	.26	.20	.23	.29	.18	.21	.19	.30	.19
U16	.24	.46	.31	.33	.30	.26	.26	.30	.24
U17	.14	.19	.18	.31	.10	.17	.23	.15	.18

Mean Correlation = .24

Split-Plane Manuevers

Inter-Individual Correlation Matrix for Guard Pilots and Instructor Weapons Systems Officers

G1 through G9 are individual Guard pilots
W1 through W4 are individual IWSOs

Rating Scores

	G1	G2	G3	G4	G5	G6	G7	G8	G9
W1	.39	.34	.46	.34	.31	.40	.33	.25	.46
W2	.30	.23	.25	.15	.18	.21	.17	.10	.25
W3	.38	.40	.44	.24	.33	.23	.41	.22	.38
W4	.45	.42	.44	.23	.30	.26	.39	.24	.45

Mean Correlation = .31

Distances in Multidimensional Space

	G1	G2	G3	G4	G5	G6	G7	G8	G9
W1	.36	.35	.48	.44	.37	.36	.38	.22	.49
W2	.18	.21	.19	.08	.12	.09	.13	.04	.24
W3	.39	.45	.55	.35	.39	.31	.49	.27	.48
W4	.49	.48	.48	.31	.39	.32	.44	.28	.49

Mean Correlation = .34

Split-Plane Maneuvers

Inter-Individual Correlation Matrix for UPTs and IWSOs

U1 through U17 are individual undergraduate pilots
W1 through W4 are individual IWSOs

	W1	W2	W3	W4
<u>Rating Scores</u>				
U1	.16	.07	.26	.19
U2	.09	.01	.14	.08
U3	.26	.10	.22	.25
U4	.20	.03	.23	.22
U5	.23	.11	.15	.11
U6	.22	.10	.23	.22
U7	.27	.10	.26	.21
U8	.16	.04	.26	.24
U9	.18	.04	.24	.25
U10	.21	.07	.20	.16
U11	.35	.12	.30	.29
U12	.22	.19	.21	.13
U13	.27	.11	.27	.24
U14	.30	.08	.33	.19
U15	.17	.09	.19	.17
U16	.30	.17	.29	.25
U17	.22	.04	.15	.15

Mean Correlation = .18

Distances in Multidimensional Space

U1	.23	.12	.29	.26
U2	.14	.03	.16	.10
U3	.27	.07	.32	.26
U4	.19	.10	.26	.22
U5	.25	.12	.19	.10
U6	.26	.05	.37	.23
U7	.33	.12	.36	.28
U8	.14	.01	.29	.25
U9	.22	.05	.32	.32
U10	.25	.05	.29	.20
U11	.29	.11	.27	.32
U12	.19	.17	.20	.24
U13	.21	.09	.31	.29
U14	.27	.06	.35	.23
U15	.12	.04	.17	.17
U16	.29	.17	.30	.27
U17	.22	.08	.20	.11

Mean Correlation = .20

Low-Angle Strafe

Inter-Individual Correlation Matrix

I1 through I6 are individual instructor pilots

Rating Scores

	I1	I2	I3	I4	I5	I6
I1	-	.49	.39	.57	.49	.41
I2	.49	-	.40	.50	.42	.39
I3	.39	.40	-	.47	.36	.31
I4	.57	.50	.47	-	.53	.45
I5	.49	.42	.36	.53	-	.42
I6	.41	.39	.31	.45	.42	-

Mean Correlation = .44

Distances in Multidimensional Space

	I1	I2	I3	I4	I5	I6
I1	-	.57	.45	.64	.51	.44
I2	.57	-	.44	.57	.41	.50
I3	.45	.44	-	.54	.44	.38
I4	.64	.57	.54	-	.53	.49
I5	.51	.41	.44	.53	-	.44
I6	.44	.50	.38	.49	.44	-

Mean Correlation = .49

Low-Angle Strafe

Inter-Individual Correlation Matrix

U1 through U16 are individual UPTs

U1 U2 U3 U4 U5 U6 U7 U8 U9 U10 U11 U12 U13 U14 U15 U16

Rating Scores

U1	-	.23	.27	.18	.22	.30	.25	.28	.24	.35	.29	.29	.29	.25	.18	.25
U2	.23	-	.40	.31	.33	.32	.33	.39	.34	.41	.30	.20	.41	.29	.29	.40
U3	.27	.40	-	.42	.24	.29	.32	.47	.37	.51	.38	.21	.38	.27	.37	.37
U4	.18	.31	.42	-	.25	.27	.27	.34	.25	.30	.28	.22	.31	.25	.37	.32
U5	.22	.33	.24	.25	-	.23	.37	.31	.23	.32	.09	.24	.21	.26	.27	.32
U6	.30	.32	.29	.27	.23	-	.40	.45	.44	.47	.25	.36	.31	.31	.33	.32
U7	.25	.33	.32	.27	.37	.40	-	.31	.41	.47	.16	.37	.39	.29	.32	.37
U8	.28	.39	.47	.34	.31	.45	.31	-	.35	.49	.31	.32	.37	.33	.40	.41
U9	.24	.34	.37	.25	.23	.44	.41	.35	-	.42	.24	.35	.36	.32	.36	.36
U10	.35	.41	.51	.30	.32	.47	.47	.49	.42	-	.29	.43	.43	.37	.40	.46
U11	.29	.30	.38	.28	.09	.25	.16	.31	.24	.29	-	.11	.27	.25	.18	.21
U12	.29	.20	.21	.22	.24	.36	.37	.32	.35	.43	.11	-	.19	.21	.24	.32
U13	.29	.41	.38	.31	.21	.31	.39	.37	.36	.43	.27	.19	-	.29	.34	.39
U14	.25	.29	.27	.25	.26	.31	.29	.33	.32	.37	.25	.21	.29	-	.29	.25
U15	.18	.29	.37	.37	.27	.33	.32	.40	.36	.40	.18	.24	.34	.29	-	.38
U16	.25	.40	.37	.32	.32	.32	.37	.41	.36	.46	.21	.32	.39	.25	.38	-

Mean Correlation = .32

Distances in Multidimensional Space

U1	-	.20	.17	.14	.29	.27	.22	.34	.18	.31	.17	.22	.26	.24	.25	.24
U2	.20	-	.41	.29	.31	.40	.36	.47	.39	.41	.20	.17	.41	.38	.27	.49
U3	.17	.41	-	.40	.27	.33	.28	.45	.23	.45	.25	.20	.36	.27	.32	.38
U4	.14	.29	.40	-	.15	.26	.17	.28	.15	.22	.14	.20	.19	.19	.27	.20
U5	.29	.31	.27	.15	-	.28	.36	.35	.23	.35	.11	.19	.29	.29	.28	.37
U6	.27	.40	.33	.26	.28	-	.44	.50	.56	.51	.22	.41	.33	.40	.31	.36
U7	.22	.36	.28	.17	.36	.44	-	.39	.43	.53	.13	.33	.45	.32	.31	.46
U8	.34	.47	.45	.28	.35	.50	.39	-	.33	.56	.28	.30	.39	.41	.44	.59
U9	.18	.39	.23	.15	.23	.56	.43	.33	-	.46	.26	.34	.40	.40	.31	.36
U10	.31	.41	.45	.22	.35	.51	.53	.56	.46	-	.24	.37	.47	.48	.42	.54
U11	.17	.20	.25	.14	.11	.22	.13	.28	.26	.24	-	.08	.13	.22	.14	.32
U12	.22	.17	.20	.20	.19	.41	.33	.30	.34	.37	.08	-	.21	.28	.20	.31
U13	.26	.41	.36	.19	.29	.33	.45	.39	.40	.47	.13	.21	-	.32	.31	.44
U14	.24	.38	.27	.19	.29	.40	.32	.41	.40	.48	.22	.28	.32	-	.29	.38
U15	.25	.27	.32	.27	.28	.31	.31	.44	.31	.42	.14	.20	.31	.29	-	.35
U16	.24	.49	.38	.20	.37	.36	.46	.59	.36	.54	.32	.31	.44	.38	.35	-

Mean Correlation = .32

Low-Angle Strafe

Inter-Individual Correlation Matrix

W1 through W7 are individual weapons systems officers

Rating Scores

	W1	W2	W3	W4	W5	W6	W7
W1	-	.43	.49	.34	.09	.56	.46
W2	.43	-	.49	.37	.19	.50	.44
W3	.49	.49	-	.39	.15	.52	.45
W4	.34	.37	.39	-	.18	.39	.29
W5	.09	.19	.15	.18	-	.17	.12
W6	.56	.50	.52	.39	.17	-	.50
W7	.46	.44	.45	.29	.12	.50	-

Mean Correlation = .36

Distances in Multidimensional Space

	W1	W2	W3	W4	W5	W6	W7
W1	-	.56	.43	.17	.46	.51	.52
W2	.56	-	.51	.12	.55	.52	.50
W3	.43	.51	-	.11	.45	.42	.39
W4	.17	.12	.11	-	.16	.11	.17
W5	.46	.55	.45	.16	-	.53	.49
W6	.51	.52	.42	.11	.53	-	.54
W7	.52	.50	.39	.17	.49	.54	-

Mean Correlation = .39

Low-Angle Strafe

Inter-Individual Correlation Matrix

I1 through I6 are individual instructor pilots
U1 through U16 are individual undergraduate pilots

	I1	I2	I3	I4	I5	I6
<u>Rating Scores</u>						
U1	.19	.16	.18	.15	.09	.21
U2	.17	.21	.28	.25	.22	.23
U3	.11	.09	.20	.16	.13	.11
U4	.12	.09	.18	.14	.09	.14
U5	.13	.16	.23	.17	.11	.16
U6	.21	.22	.22	.21	.28	.32
U7	.14	.17	.31	.21	.26	.22
U8	.23	.19	.26	.22	.23	.27
U9	.17	.14	.33	.18	.29	.27
U10	.30	.29	.41	.32	.32	.27
U11	.06	.03	.11	.04	.00	.11
U12	.29	.20	.26	.28	.26	.28
U13	.21	.21	.25	.21	.32	.22
U14	.13	.14	.32	.20	.23	.21
U15	.10	.18	.35	.14	.18	.23
U16	.15	.13	.30	.24	.23	.13

Mean Correlation = .20

Distances in Multidimensional Space

U1	.22	.24	.20	.20	.17	.19
U2	.23	.25	.30	.23	.29	.21
U3	.10	.12	.23	.18	.11	.06
U4	.11	.11	.19	.13	.09	.05
U5	.12	.20	.27	.21	.15	.18
U6	.21	.19	.25	.24	.30	.30
U7	.19	.19	.35	.25	.29	.21
U8	.22	.22	.34	.28	.30	.27
U9	.19	.17	.28	.18	.26	.28
U10	.29	.31	.45	.35	.34	.26
U11	.08	.04	.15	.08	.03	.04
U12	.37	.29	.31	.38	.34	.30
U13	.24	.18	.24	.21	.27	.15
U14	.21	.20	.37	.25	.34	.25
U15	.19	.16	.36	.21	.20	.25
U16	.21	.19	.34	.30	.23	.11

Mean Correlation = .22

Low-Angle Strafe

Inter-Individual Correlation Matrix

I1 through I6 are individual instructor pilots
W1 through W7 are individual weapons systems officers

Rating Scores

	I1	I2	I3	I4	I5	I6
W1	.40	.40	.42	.52	.54	.44
W2	.38	.32	.44	.44	.45	.34
W3	.50	.43	.50	.54	.45	.48
W4	.36	.38	.42	.40	.39	.38
W5	.05	.11	.18	.05	.05	.16
W6	.45	.45	.51	.61	.46	.45
W7	.45	.45	.34	.51	.46	.47

Mean Correlation = .39

Distances in Multidimensional Space

	I1	I2	I3	I4	I5	I6
W1	.40	.36	.48	.48	.47	.35
W2	.51	.48	.52	.63	.45	.44
W3	.39	.45	.53	.45	.43	.38
W4	.16	.15	.14	.12	.03	.26
W5	.44	.49	.51	.55	.52	.46
W6	.46	.50	.55	.62	.47	.52
W7	.51	.54	.42	.57	.43	.45

Mean Correlation = .43

Low-Angle Strafe

Inter-Individual Correlation Matrix

U1 through U16 are individual undergraduate pilots
W1 through W7 are individual weapons systems officers

	W1	W2	W3	W4	W5	W6	W7
<u>Rating Scores</u>							
U1	.20	.24	.21	.21	.13	.22	.16
U2	.26	.36	.24	.30	.18	.31	.25
U3	.15	.27	.16	.23	.20	.26	.11
U4	.14	.22	.15	.16	.23	.23	.09
U5	.21	.25	.20	.21	.16	.19	.16
U6	.25	.36	.30	.23	.18	.36	.29
U7	.31	.40	.21	.30	.15	.33	.22
U8	.28	.37	.25	.25	.19	.35	.28
U9	.26	.28	.22	.31	.14	.33	.23
U10	.35	.45	.41	.33	.20	.44	.28
U11	.06	.08	.13	.10	.07	.15	.03
U12	.28	.33	.33	.35	.10	.30	.24
U13	.33	.33	.20	.25	.09	.32	.21
U14	.27	.30	.22	.23	.17	.30	.22
U15	.26	.26	.17	.21	.26	.30	.14
U16	.26	.32	.26	.31	.14	.29	.18

Mean Correlation = .24

Distances in Multidimensional Space

U1	.23	.15	.21	.15	.25	.26	.30
U2	.41	.23	.29	.16	.26	.28	.35
U3	.25	.18	.20	.08	.14	.21	.19
U4	.20	.09	.12	.09	.07	.18	.11
U5	.30	.25	.22	.12	.29	.29	.26
U6	.35	.26	.28	.11	.25	.37	.28
U7	.33	.25	.26	.06	.31	.39	.25
U8	.46	.28	.31	.12	.37	.36	.32
U9	.27	.23	.32	.11	.25	.36	.25
U10	.45	.41	.34	.10	.37	.50	.34
U11	.05	.17	.21	.01	.08	.10	.08
U12	.31	.38	.39	.06	.33	.42	.26
U13	.30	.22	.21	.03	.27	.28	.24
U14	.32	.26	.28	.15	.29	.32	.31
U15	.33	.20	.28	.23	.29	.35	.22
U16	.40	.31	.38	.05	.34	.34	.26

Mean Correlation = .25